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OPTIMIZATION FOR HUMAN SYSTEMS INTEGRATION

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NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

OPTIMIZATION FOR HUMAN SYSTEMS INTEGRATION

by

Joseph D. Novak

September 2021

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13. ABSTRACT (maximum 200 words)

The stated objective of Human Systems Integration (HSI) in the DOD is optimization, specifically to maximize total system performance and minimize cost. Limited published precedents describe quantitative optimization across the HSI domain trade-spaces.

The Model-Based HSI (MBHSI) process utilizes General Systems Performance Theory to relate HSI domain resource inputs to total system performance output. MBHSI also recharacterizes each domain in terms of constructs that are amenable to optimization via mathematical programs (MP). However, MBHSI does not provide an archetypal optimization model or method. This work pursues quantitative HSI optimization models and a method for creating those models in order to facilitate real-world tradespace decisions between the personnel, training, and human factors engineering domains.

This work presents an MP formulation and solves it using an MBHSI data set and notional cost data. Sensitivity analyses further elucidate the trade space, and follow-on analyses demonstrate solution set changes based on varying resources, constraints, and cost parameters. Results indicate that MBHSI enables MP formulation and data set optimization.

Decision makers are perpetually making trade-off decisions between HSI domains, many times without quantitative knowledge of the trade-space. MBHSI-derived MPs may enable responsive and evidence-based system change decisions in order to quantitatively achieve the stated goal of HSI—optimization.

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OPTIMIZATION FOR HUMAN SYSTEMS INTEGRATION

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Submitted in partial fulfillment of the
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LIST OF ACRONYMS AND ABBREVIATIONS

ANAM	Automated Neuropsychological Assessment Metrics
BPR	Basic Performance Resource
DAS	Defense Acquisition System
DAU	Defense Acquisition University
DOD	Department of Defense
DODD	Department of Defense Directive
DODI	Department of Defense Instruction
DSOC	Defense Safety Oversight Council
DV	Dependent Variable
FAA	Federal Aviation Administration
FR	Functional Requirement
GSPT	General Systems Performance Theory
HFE	Human Factors Engineering
HLT	High-Level Task
HLTp	High-Level Task Performance
HSI	Human Systems Integration
INCOSE	International Council on Systems Engineering
IV	Independent Variable
LP	Linear Programming
MBHSI	Model-Based Human Systems Integration
MBSE	Model-Based Systems Engineering
MINLP	Mixed-Integer Non-Linear Program
MP	Mathematical Program
NCRA	Nonlinear Causal Resource Analysis
NPS	Naval Postgraduate School
NDS	National Defense Strategy
NSS	National Security Strategy
OR	Operations Research
PCE	Performance Capacity Envelope
PM	Program Manager

R_A	Resource Availability
R_D	Resource Demand
RDF	Resource Demand Function
SE	Systems Engineering
TTAMs	Tools, Techniques, Approaches, and Methods
TSP	Total Systems Performance
TST	Trade Space Tool
USAF	United States Air Force

EXECUTIVE SUMMARY

The stated objective of Human Systems Integration (HSI) in the Department of Defense (DOD) is optimization—specifically, to maximize total system performance and minimize cost (DAU, n.d.). This research work demonstrates quantitative HSI optimization on an aircraft simulator test case using data from the Model-Based HSI (MBHSI) process.

The DOD tasks HSI to account for the unique qualities of the humans who interact with weapons systems, and to inform the design of said systems. HSI trades occur across seven or more constituent domains in order to achieve optimization. The Naval Postgraduate School's definition of HSI states that HSI "makes explicit the underlying trade-offs across the HSI domains" (Tvaryanas & Shattuck, 2010), yet there are limited published precedents that describe quantitative trades across these domains. HSI faces many challenges in carrying out optimization, including lacking standardized processes and semantics for domain tradespace management and, until recently, lacking a theoretical framework linking HSI resource inputs with total system performance output (Tvaryanas, 2010).

The MBHSI process, introduced by Taranto (2020), utilizes General Systems Performance Theory (GSPT) (Kondraske, 2011) to relate HSI domain resource inputs to total system performance output. MBHSI also recharacterizes each HSI domain in terms of standardized constructs that are amenable to optimization via mathematical programs (MPs). However, MBHSI does not provide an archetypal optimization model or method. This work pursues a quantitative HSI optimization model and a method for creating such models based on the output of MBHSI and GSPT. The specific thesis research questions are as follows:

> Can we apply MPs to the models and data produced by Taranto's (2020) MBHSI experiment? If so, how can these MPs enable quantification of the HSI tradespace and enable decision-makers to minimize cost and maximize performance?

The thesis MP addresses tradespace questions that HSI practitioners must answer in daily practice. As such, the MP focuses on the Personnel, Training, and Human Factors

Engineering (HFE) domains, and utilizes the experimental setup and data from Taranto (2020) as a surrogate for a real-world tradespace problem. Taranto measured "high-level task" performance on an aircraft simulator flying event and related that score to test subject scores on basic "lower-level" capacities (such as spatial awareness, limb coordination, and math processing speed) via a GSPT approach. In this way, he connected HSI resource input (test subject capacities) to total system performance output (high-level task performance).

We designed a mixed-integer nonlinear program (MINLP) that enables explicit trades between the Training, Personnel, and HFE domains as characterized by MBHSI. Decision variables are subjects selected (binary 0, 1) and high-level task performance for each selectee (continuous). The MP utilizes notional cost data for the domain parameters. Constraints enforce an exact number of selectees, a minimum high-level task performance for each selectee, and an average high-level task performance value for the selectee cohort. We ran the MINLP for five different performance target scenarios and then performed a sensitivity analysis on each scenario. Results indicate that MBHSI enables MP formulation and data set optimization.

This thesis ultimately operationalizes the creation of MPs, using those data that result from the MBHSI process to efficiently manage Training, Personnel, and HFE resources. The MINLP and its solutions answer the thesis research questions posed by quantifying the selected HSI tradespace and yielding results which minimize cost for targeted levels of performance for the system described in Taranto's experiment.

The optimization formulation demonstrates the potential to explicitly address the tradespace problem between select HSI domains. The MP is system, task, and life cycle phase agnostic. Similar MPs may be applicable to real-world HSI tradespace problems after additional work and research in this area by systems engineers, HSI practitioners, and OR experts. If these MPs can be scaled and utilized at the program, service, and DOD level, they may be able to help decision makers increase total system performance and decrease costs by providing a quantitative understanding of the tradespace. These types of MPs could bring the DOD closer to the stated objective of HSI—optimizing total system performance and minimizing cost.

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I owe everything to my father and mother, two incredible parents, patriots, and citizens. My parents escaped communist Czechoslovakia and started their lives in America with nothing but hard work, determination, and love. They had three children, led exemplary lives, and are the archetypal American success story. They gave me every tool I could ever need in life and, along with my brother and sister, were there for me during every trial and challenge. I am the luckiest man in the world to have had them as my parents. Rest in peace Dad, Semper Fidelis, and thank you for everything.

My team of advisors was second to none. Across the board, they were incredibly responsive, helpful, and generous with their time. Exemplifying everything you would want in an advisor is Dr. Louis Chen. Both the formulation and code (i.e., the heart of this thesis) would simply not have been possible without Dr. Chen's optimization expertise and willingness to help. We spent countless evenings and nights working, and I recall several times after midnight on the weekends where I would text or email Dr. Chen, and seemingly have a reply as soon as I hit send! Dr. Robert Koyak, your wisdom and centering presence always helped me see the big picture. Your knowledge of prior MBHSI work was essential in this follow-on effort, and your patience was truly appreciated. Mike O'Neil, thank you for your responsiveness, attention to detail, and helping to turn this work into a thesis. Your guidance was vital in keeping this work relevant to HSI stakeholders.

This research was built on the shoulders of many who have come before, of particular note are Dr. Anthony Tvaryanas, Dr. George Kondraske, and Dr. Matthew Taranto. Dr. Tvaryanas, your piercing intellect, pioneering vision, and clarity of thought changed my views on HSI, among many other things, and I am thankful for the trails you have blazed. Dr. Kondraske, I find your body of research work, namely GSPT, refreshingly

insightful and revolutionary. I believe that we are just seeing the tip of the iceberg regarding the implications of GSPT. Dr. Taranto, how you weaved together so many concepts and disciplines to create MBHSI is still beyond me. Your cutting-edge dissertation is an inspiration and birthed research that must be continued for the good of our soldiers and our country. Also, thank you for your hundreds of hours of mentorship, instruction, guidance, and feedback. I hope that this thesis continues to spread the word of MBHSI and furthers the applicability to the services.

I have had a blessed career in the USAF, and I owe that largely to the extraordinary leadership I have had. Col David Slade (retired) and General David Goldfein (retired), you signed the papers that allowed me to pause flying the F-15C in order to attend medical school. This thesis and this HSI degree are key milestones in the journey that started way back then. With the knowledge I have gained at NPS, I hope that I can coalesce my engineering, operational, and medical experience and uniquely contribute to the USAF as you intended. Brigadier General Mark Koeniger, you sent me to NPS with one charge... to research how to quantify HSI and determine HSI's return on investment. Major General Sean Murphy, you were always supportive and reassuring when the road to NPS looked questionable. Thank you both for your faith in me and your support throughout the years.

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I. INTRODUCTION

Every day, millions of independent tasks initiated by thousands of units across the globe combine to enable and carry out the Department of Defense's (DOD) wide-ranging mission of national defense. The human system is the one element all these tasks have in common. Humans operate, maintain, and support all DOD systems. While the goal can be elusive, keeping the human a top priority in all aspects of DOD systems is essential. This focus on the human actor is the distinguishing feature of Human Systems Integration (HSI).

HSI is a human-focused, DOD-defined, multi-domain discipline within systems engineering. The goal of HSI is to optimize total system performance (TSP) and minimize costs for DOD systems (Defense Acquisition University [DAU], n.d.). HSI treats the unique characteristics and capabilities of human operators, maintainers, and support personnel as fundamental design considerations for DOD systems. The DOD can begin to optimize TSP and minimize costs by making explicit the underlying trade-offs between the recognized HSI domains of manpower, personnel, training, human factors engineering, safety and occupational health, force protection and survivability, and habitability (Tvaryanas & Shattuck, 2010).

In a broad sense, HSI provides a means of giving humans equal consideration with technology during system design, development, analysis, and utilization. Humans operate, maintain, and support all systems in the DOD, so it follows that the goal of "optimizing TSP" must jointly consider these humans and the technologies with which they interact. If the DOD does not optimize the use of human capabilities by applying the tenets of HSI, total system effectiveness may degrade, and costs may substantially increase and compound over the course of the system's life cycle. Hence, HSI is critical for DOD success.

DOD Directive (DODD) 5000.01, *The Defense Acquisition System*, is the highest-level directive that manages the cradle-to-grave life cycles of military systems that support the *National Security Strategy* (White House, 2017). This directive outlines the importance of a systems engineering approach that "optimizes total system performance and minimizes total ownership costs" (Department of Defense [DOD], 2018, p. 9). Section E1.1.29 underscores this point by stating, “The PM [program manager] shall apply human systems integration to optimize total system performance (hardware, software, and human), operational effectiveness, and suitability, survivability, safety, and affordability” (p. 10).

Likewise, Enclosure 7 of DOD Instruction (DODI) 5000.02, *Operation of the Defense Acquisition System*, describes the goal of HSI: “to optimize total system performance and total ownership costs” (DOD, 2017, p. 124). The forthcoming DODI 5000.02PR, *Human Systems Integration in Defense Acquisition*—soon to replace Enclosure 7 of DODI 5000.02—maintains, “It is DOD policy that . . . HSI in defense acquisition provide a disciplined, unified, and interactive approach to integrate human considerations into system design to optimize total system performance and minimize life-cycle costs” (DOD, 2020b, p. 3). Thus, from the highest-level DOD policy directives, the call for “optimization” in HSI is clear. However, its implementation is not trivial.

While the importance of HSI is obvious, the means for executing it are not. As a discipline, HSI faces many challenges (Booher, 2003). Dealing with DOD system complexity and advocating for the human actors in a DOD program office are substantial undertakings (United States Air Force, 2012). Furthermore, because the conceptual understanding of HSI varies widely, HSI is difficult to execute. Thus, the practice of HSI differs, evidenced by the inconsistency of fundamental terms and semantics, the lack of standardized processes and best practices, and variance in tools, techniques, and methods for optimizing TSP (Riker, 2019; Tvaryanas, 2010; Shattuck et al., 2011; Taranto, 2020; O’Neil, 2014). At a basic level, to optimize design and make trades between domains—the role of HSI—standardized semantics, quantifiable values in comparable units, quantifiable relationships between the domains, and a theoretical basis connecting system inputs and outputs are needed.

Introduced in 2020, Model-Based Human Systems Integration (MBHSI) is an HSI empirical modeling process that recharacterizes HSI domains using standardized, inter-domain compatible constructs derived from General Systems Performance Theory (GSPT) (Taranto, 2020). Taranto (2020) built on Tvaryanas’ (2010) HSI dissertation and Kondraske’s (2011) GSPT to develop MBHSI as a theory-based, standardized process. MBHSI employs an empirical model that characterizes the relationships between the HSI domains (inputs) and TSP (output). These relationships between system inputs and output are required to optimize

HSI via mathematical programs (MP). MBHSI also proposes standardized semantics, quantifies system input and output values in comparable units, quantifies relationships between HSI domains, and utilizes GSPT as a theoretical basis to connect human considerations (system inputs) with TSP (system outputs).

While Taranto (2020) discusses the potential of MBHSI to inform the creation of MPs, he left explicit formulation of actual MP examples for follow-on research. This thesis explores the application of MPs to Taranto's MBHSI experiment results in order to optimize the experimental TSP and minimize notional costs. Figure 1 depicts the interrelatedness of MBHSI and GSPT, Operations Research (OR), and Model-Based Systems Engineering (MBSE)/Systems Engineering (SE). This thesis resides within the OR "cog."

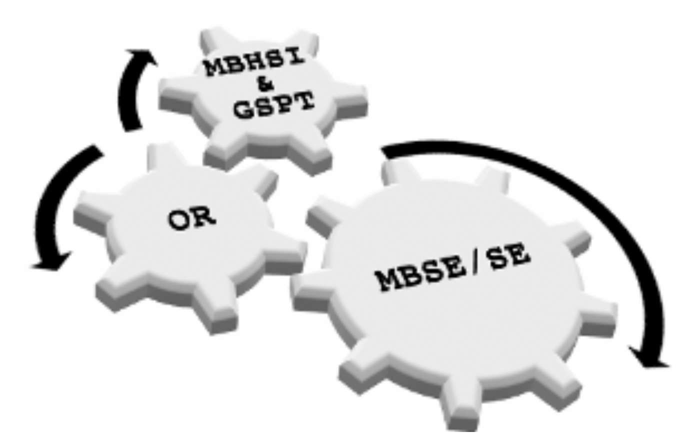

Figure 1. Relationship between Operations Research, MBHSI, and MBSE. Source: Taranto (2020, p. 192).

A. PROBLEM STATEMENT

MBHSI shows promise in quantifying relationships between HSI domain resources (inputs) and total system performance (output) using a threshold-based approach to performance forecasting. MBHSI delivers HSI outputs for systems engineering (SE), as illustrated in Figures 1 and 3. In 2020, MBHSI techniques were used in an aircraft simulator setting to quantify relationships between HSI independent variables (e.g., individual human performance capacities) and dependent variables including system performance and cost. The experiment succeeded in very accurately predicting high-level task performance among the test subjects (Taranto, 2020, p. 113). However, HSI stakeholders lack effective methods to optimize and operationalize the insights and data provided by MBHSI. This current MBHSI capability gap might be solved by developing MPs that use MBHSI outputs to define HSI decision variables, objective functions, and constraints in order to calculate optimal solution sets. If successful, MBHSI-derived MPs may increase the capacity of HSI to communicate with and provide value to its containing (i.e., "parent") systems of SE and the Defense Acquisition System (DAS).

B. PURPOSE OF THE STUDY

This study focuses on determining whether the models and data created as an output of MBHSI are compatible with mathematical programming approaches for optimization. If feasible, MPs could enable quantitative trades among the different HSI domains to achieve optimal TSP at minimal cost.

Taranto's (2020) dissertation resulted in a rich data set that this thesis explores using MPs. MBHSI outlines explicit relationships and relates human resources to TSP; describes and quantifies these relationships; and may help predict the engineering triad of cost, schedule, and performance. The predictive capabilities of MBHSI result in dependent variable values based on the independent variables. In a dynamic, multi-variable real-world system, the latter can be manipulated to achieve desired dependent variables. But how does one determine the number, mix, and values of the independent variables to achieve desired dependent variables? Optimization using MPs is one way to achieve this end. Thus, a logical next step for MBHSI is to determine whether the MBHSI process model and resultant data lend themselves to optimization via MILP.

C. RESEARCH QUESTION

1. Conceptual Questions

Is it possible to apply MPs to MBHSI process outputs? If so, how can these MPs quantify the HSI tradespace and inform the DOD-stated objective of HSI (optimization) and the goal of MBSE/SE (performance)?

2. Thesis Questions

Can we apply MPs to the models and data produced by Taranto's (2020) MBHSI experiment? If so, how can these MPs enable quantification of the HSI tradespace and enable decision-makers to minimize cost and maximize performance?

D. RESEARCH APPROACH

This study, creating and applying MPs to the output of an MBHSI use case, approaches the problem using known SE thesis archetypes. The chosen methods then ensure both tractability and relevance.

1. Thesis Framework

Giachetti (2016) categorizes SE theses as experimental, empirical, design, analytical, or combinations thereof. HSI operates within SE as a sub-discipline, so adapting these overarching approaches to the problem is appropriate. Broadly speaking, this thesis supports these objectives by combining design, analysis, and theory-driven components (Giachetti, 2016; Petre & Rugg, 2010). Design artifacts include formulation of new MPs for HSI tradespace problems using MBHSI and GSPT constructs and methods to derive them. Next, analysis focuses on solving and verifying the MP models. Last, the theory-driven aspect of this thesis "extends an existing [theory], and may rely on argument, analysis, and illustrative examples, or may draw on empirical evidence" to extend the theory of GSPT and the process of MBHSI (Petre & Rugg, 2010, p. 26).

2. Method and Results Overview

We designed the MP in this thesis to address tradespace questions that HSI practitioners must answer in daily practice. The MP addresses the Personnel, Training, and Human Factors Engineering (HFE) domains, utilizing the experimental setup and data from Taranto (2020). Taranto (2020) measured "high-level task" performance on an aircraft simulator flying event and related that score to the test subjects' scores on basic "lower-level" tasks via a threshold-based approach. The data were captured in a spreadsheet and determined not to involve human subjects research by the Institutional Review Board. Sixty-four subjects were first tested on 19 basic performance resources including items such as spatial awareness, multi-limb coordination speed, and math processing speed. The subjects were then scored on two instrument landing system approaches in a Cesna-172 flight simulator. The data were continuous ratio data in defined units.

We created the MP utilizing the relationships defined through the MBHSI process and Taranto's experiment. The personnel, training, and HFE cost parameters were notional. The MP was then programmed into the Julia and JuMP programming languages. We solved the MP for five different scenarios using the basic task data from Taranto's (2020) 64 subjects. Results yielded the subjects who were the optimal fit (i.e., lowest cost) along with their performance scores for the given scenarios.

E. SIGNIFICANCE TO THE FIELD

Often, the relationship between human capacities and system performance is nebulous, ill-defined, or unquantifiable. Tvaryanas (2010) states, "It is the rare case indeed where HSI-type constraints can be developed based on intuition, first principles, natural laws, or other empirical regularities. . . . They must develop the necessary main constraint(s) from an empirical dataset" (p. 21). Additionally, HSI practitioners come from various backgrounds with different levels and types of training. Many do not have experience in modeling or quantitative methods. As Tvaryanas and Shattuck (2010) state,

> While most HSI students—and many HSI practitioners for that matter—are comfortable making qualitative trade-offs (e.g., if I decrease personnel quality, I will need to increase training), progressing to quantitative trade-offs often remains a significant stretch. . . .Additionally, quantitative trade-offs are largely the subject matter of the mathematical programming half of operations research, but the vast majority of those working in HSI have no exposure to undergraduate- or graduate-level operations research courses. (p. 1)

This thesis operationalizes the creation of MP optimization formulations using those data that result from the MBHSI process. The MBHSI process utilizes GSPT as the theoretical framework to model the human system and quantify the relationship between HSI domain resources (in the form of human capacities) and system performance. Kondraske and others have tested and utilized the theory of GSPT in multiple studies over several decades (Kondraske, 2019). Taranto's (2020) dissertation demonstrated the MBHSI process by using a flying simulation test case. MBHSI can be used to derive the empirical data set that Tvaryanas (2010) refers to, by taking HSI domain resource inputs and establishing a quantitative relationship with outputs (performance) via GSPT.

For this thesis, we used Taranto's (2020) MBHSI data set to demonstrate an MBHSI mathematical program formulation. Figure 2, from Taranto (2020), shows how mathematical program formulation flows from MBHSI outputs. This research carries out the flow diagram, especially from "Quantify resources" to "A Linear Program." With continued research and scaling, this type of approach may provide decision makers with a novel empirical method for achieving the DOD's stated objective of HSI: optimizing total system performance and minimizing cost (DAU, n.d.).

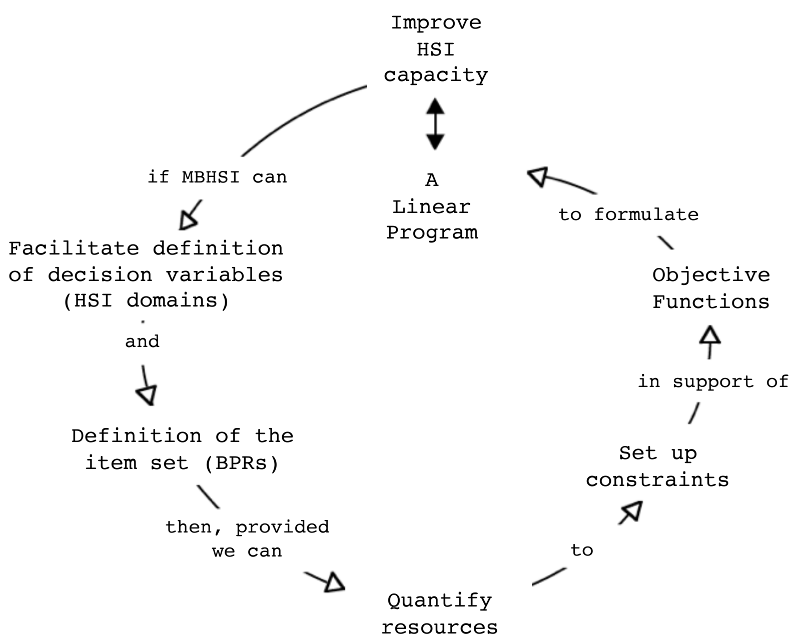

Figure 2. Using MBHSI to facilitate mathematical program formulation. Source: Taranto (2020, p. 183).

F. SIGNIFICANCE TO THE UNITED STATES AIR FORCE

This researcher was sent to the Naval Postgraduate School (NPS) for a Master of Science in Human Systems Integration, with one charge from his highest-ranking sponsors. The 711th Human Performance Wing Commander, a Brigadier General, specifically challenged the author to research ways to quantify the value that HSI provides (personal communications and emails, June 2017–May 2019). Prior to the Fall of 2019, the United States Air Force (USAF) had an entire Directorate dedicated solely to HSI. The USAF senior leaders wanted to analyze and justify the HSI Directorate's cost in manpower, time, and effort. We conducted this research to work towards that goal.

Many of the tenets of MBHSI are echoed in the USAF Chief of Staff's strategic direction for the service. In August 2020, incoming USAF Chief of Staff General Charles Brown published the modus operandi for his tenure, entitled "Accelerate Change or Lose" (Brown, 2020). In it, he discusses multiple concepts inherent in MBHSI and optimization, such as the importance of performance, trade-offs, and personnel concerns. "We must be able to frame decisions and trade-offs with both a near and long-term view of what value our capabilities provide throughout the life cycle of performance" (p. 6). He also directed the USAF to "reward and retain those Airmen who foster the personal attributes necessary for success in the challenging future ahead" (p. 6). Finally, like Brigadier General Koeniger, General Brown emphasizes the value of the USAF's investments: "We must . . . ensure that the U.S. Air Force is gaining the most value and being good stewards of taxpayer dollars" (p. 5). This thesis pursues these goals by striving to optimize the output of MBHSI.

II. BACKGROUND AND LITERATURE REVIEW

Before discussing the approach to HSI via MBHSI, we will examine the larger context within which HSI operates. The U.S. DOD is a massive organization that uses the Defense Acquisition System (DAS) to acquire weapons systems, systems engineering (SE) to build weapons systems, and HSI to account for the humans in the weapons systems, while optimizing total system performance and minimizing cost. Figure 3 demonstrates the relationships between these different systems and their interactions (Model-Based Systems Engineering [MBSE] and SE will be considered synonymous for the purposes of this thesis). This thesis work lies between MBHSI and MBSE and is symbolized by the leftward-pointing arrow. Chapter III covers MBHSI and GSPT in depth, while the following sections cover the containing systems shown in Figure 3.

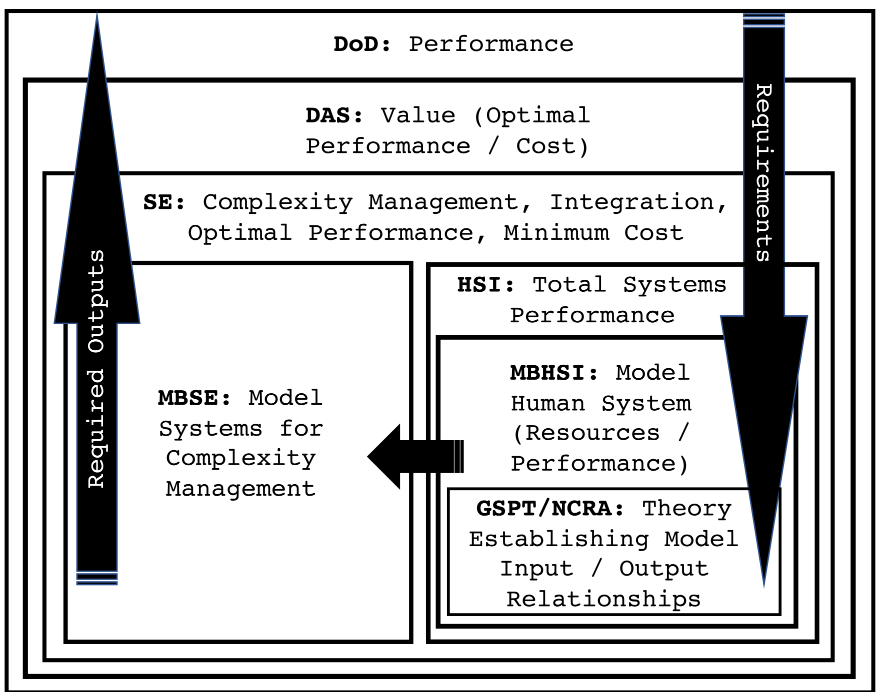

Figure 3. Relationships and hierarchies among the DOD, DAS, SE, and HSI. Source: Taranto (2020, p. 15).

A. DEPARTMENT OF DEFENSE

The DOD is the most powerful military organization the world has ever known, with an incredible amount of complexity inherent in its operations due to its mission and sheer size. The DOD "is responsible for providing the military forces needed to deter war and to protect the security of our country" (White House, n.d.). Subordinate to the Executive Branch of the federal government, the DOD coordinates and runs all agencies and functions of the U.S. government directly related to national security. The DOD is the largest employer in the world with nearly 3.5 million part- or full-time employees, including just under 1.3 million active-duty members (DOD, 2017a). With an annual budget of $714 billion in FY2020 (Government Accountability Office, 2021), the U.S. DOD spends more than most countries' entire budgets, and more than the next seven largest defense budgets combined (Koop, 2021).

As depicted in Figure 3, the DOD relies on the DAS, which produces and manages DOD weapons systems from inception to retirement. The following sections consider the DAS, SE, and their relationship to HSI.

1. Defense Acquisition System

The DAS is the cradle-to-grave management process for DOD weapons systems. It is the method by which the DOD identifies operational capability gaps, materiel (or other) ways to address the gaps, and the requirements; analyzes potential solutions; designs and develops the best solutions; verifies, validates, fields, and supports the solutions during their life cycle; and then disposes of them upon retirement. According to the *Defense Acquisition Guidebook*, "The Defense Acquisition System exists to manage the Nation's investments in technologies, programs, and product support necessary to achieve the National Security Strategy and support the United States Armed Forces" (DAU, n.d., Foreword, p. 1). Managing the nation's investments is a complex process that involves dozens of domains and challenges, including operations, logistics, testing and evaluation, intelligence, software, finance, interoperability, politics, engineering specialties, contracting, and more. Such complexity justifies the need for a disciplined systems development, production, and sustainment framework, and SE is the chosen discipline to enable this structure.

2. Systems Engineering

SE is a disciplined problem-solving approach that focuses on emergence and the whole system rather than the component subsystems. For the DOD, SE "establishes the technical framework for delivering materiel capabilities to the warfighter . . . [and] provides the foundation upon which everything else is built and supports program success" (DAU, n.d., chapter 3, p. 1). The general process of SE involves understanding the problem, examining the alternatives, designing a solution, verifying and validating the solution, and delivering the solution while recognizing the constraints of cost, schedule, performance, and risk.

The complexity of DOD systems necessitates the SE approach. As mandated in DODI 5000.88, *Engineering of Defense Systems*, "The DOD will conduct a comprehensive engineering program for defense systems... The engineering management activities include... systems engineering" (2020a, p. 4). Furthermore, the SE approach for the DAS is codified in the systems engineering plan, "which provides a foundational engineering approach for all technology-based programs" (2020a, p. 4). Alongside other engineering specialties, HSI forms part of the SE process in the DAS.

B. HUMAN SYSTEMS INTEGRATION

HSI's role in DOD policy is compatible with its containing systems—SE and the DAS—as shown in Figure 3. The DOD (2017b) requires that "HSI in defense acquisition provide a disciplined, unified, and interactive approach to integrate human considerations into system design to optimize total system performance and minimize life-cycle costs" (p. 1). "Human considerations" refers to any interactions between humans and a system, and the "humans" include operators, maintainers, supply personnel, and administrators who may be active-duty, reserve, contractor, or government service members. Human considerations comprise several HSI domains that vary slightly among the services: manpower, personnel, training, HFE, force protection and survivability, safety and occupational health, and habitability (Department of Defense, 2020b).

1. Origins and Brief History

The emphasis on HSI and adherence to its tenets have varied over the years. The initiatives that eventually became HSI originated in the U.S. Army in the late '60s and early '70s. Tvaryanas (2010) suggests that HSI policy and programs started as a response to the increasing complexity and skyrocketing costs of weapons systems:

> HSI as a philosophy evolved within the context of the larger systems movement that occurred in the 1960s in response to the issue of irreducible complexity. HSI emerged in response to real-world, macroergonomic, political and military challenges that resulted in an organizational crisis. This crisis, in the simplest of terms, was caused by technological complexity and its effects on personnel. Thus, the fundamental impetus for HSI was complexity. (p. 531)

Moreover, as Tvaryanas and Shattuck (2010) explain, "The recognition of the interdependence of the HSI domains, and thus the need to consider domain trade-offs, was a critical driver in the emergence of HSI within the U.S. Defense Department" (p. 1). HSI then formally began in the Army in the 1980s, with the other services following suit (for more on the history of HSI, see Tvaryanas (2020) and Booher (2003)).

2. HSI's Role in the DOD

The role of HSI is to optimize total system performance (TSP) and minimize costs for DOD systems while operating across several domains (DAU, n.d.). By making explicit trades between the recognized HSI domains, the DOD can work towards these aims. According to the DOD, "Trade-off analyses ensure human performance data systematically informs and facilitates total system performance in both materiel and non-materiel solutions during systems engineering activities" (DOD, 2020b, p. 5).

3. Optimization and Trade-offs in HSI Policy

Optimization and trade-off analyses are omnipresent themes among the numerous formal definitions and explicit objectives of HSI laid out in DOD policy. The most common phrasing for the goal of HSI is "to optimize total system performance and minimize cost." Definitions of HSI universally include derivatives of the words "optimize," "minimize," and "trades," as can be seen in the Appendix (DOD, 2018, p. 8; DOD, 2020b, p. 3; DOD, 2017b, p. 19; DAU, n.d., chapter 5, p. 1; NPS, 2021). This uniformity in defining the explicit purpose of HSI leaves no doubt as to the importance of the concept of optimization to the field of HSI.

4. Mathematical Optimization for HSI

Optimization is a term that carries multiple meanings depending on context and discipline. Tang highlights several interpretations of optimization in engineering, including "refinement" and "continuous improvement" (Tang, 2021, p. 183). Continuous improvement and refinement are gradual, ongoing, and can be executed by non-specialists in a variety of ways. Optimization seeks the best status given constraints, and is typically carried out by specialists (Tang, 2021). This thesis work focuses on quantifiable optimization as described by Tang and the field of OR.

According to Tvaryanas (2010), complexity—of technology and its impact on human actors—has been a key driver for the creation of HSI (p. 530). Complexity also compelled George Dantzig to create the fundamental theories of mathematical programming, which formed the basis of OR (Dantzig & Thapa, 2006). Thus, the optimization techniques of OR, particularly MPs, may assist HSI in addressing tradespace challenges.

The purpose of every MP is to maximize or minimize an objective function, subject to various constraints (Rardin, 2017, p. 4). This optimization is accomplished by formulating an MP. Formulating an MP requires several components: an objective function, decision variables (DVs), constraints, and data/parameters (Tables 6–10 present this work's MP broken down in this way). The objective function mathematically describes what must be optimized, often a function of cost. The decision variables can then be manipulated in order to optimize the objective function. The constraints limit the potential values of the DVs and thus "constrain" solutions to the objective function. The data and parameters are then used to quantify the problem space. There are different types of MPs for different types of problems, many of which may be relevant to the HSI tradespace.

As shown with the recurring theme of optimization in the previous definitions, the DOD's stated goal for HSI is optimization. If HSI domain input parameters and system output (performance) can be quantified and related using a predictive model, then MPs may perform these HSI optimizations (Figure 11). This type of theoretically based predictive model, however, has been elusive in HSI. Notably, while theories and even laws have modeled and predicted intra-domain phenomena, inter-domain relationships have been difficult to describe, with few examples in the literature.

5. Previous Optimization Work in HSI

As of this writing, few published examples of MPs constructed for the purposes of HSI could be found. Tvaryanas (2010) and Tvaryanas and Shattuck (2010) formulated HSI MPs, but the scope of their formulations and applicability to HSI domain trades were limited. Tvaryanas and Shattuck (2010) created an MP based on Fitts's law, which relates operator response time to target buttons on a control panel. The objective function resulted in the values of the button width and separation that minimized the total width of the control panel, subject to various constraints. This example was an intra-domain HFE use of an MP, but did not relate the HSI domains to each other. Tvaryanas (2010) related biomathematical fatigue models to a scheduling problem in order to minimize a manpower objective function. This formulation implicitly allowed for trades between the manpower, survivability, habitability and HFE domains and was perhaps the first example using an MP to address an HSI tradespace problem. However, Tvaryanas' MP was "custom made" for this particular example and lacked a theory that accounted for inter-domain relationships. Both these formulations thus lacked a standardized method to characterize mathematical relationships between HSI domains.

Miller et al. (2007) created a software package called the HSI Trade Space Tool (TST), which was "designed to help HSI practitioners, program managers, and other acquisition professionals visualize the relationships among: the HSI domains . . . the dimensions of cost, schedule, and risk, and the result of Total System Performance" (abstract). This program has been recently upgraded and helps to visualize and manipulate the HSI tradespace, as shown in Figures 4 and 5. The program illustrates user-defined mathematical relationships between two domains at a time and can incorporate up to four domains along with cost, schedule, performance, and risk. For example, Figure 4 illustrates that as one receives more training, their required “FAST score” (a measure of fatigue) can decrease. The TST is useful for visualization purposes and to illustrate user-defined domain relationships. It is also useful as a means of educating practitioners to the potential power of MPs. A partial “optimization” is possible by manipulating input variables, but only for one constraining relationship in each selected domain. Also, users must determine the mathematical relationships that connect the HSI domains, and a connection to TSP, HSI domain resources, and individuals is not required or enforced.

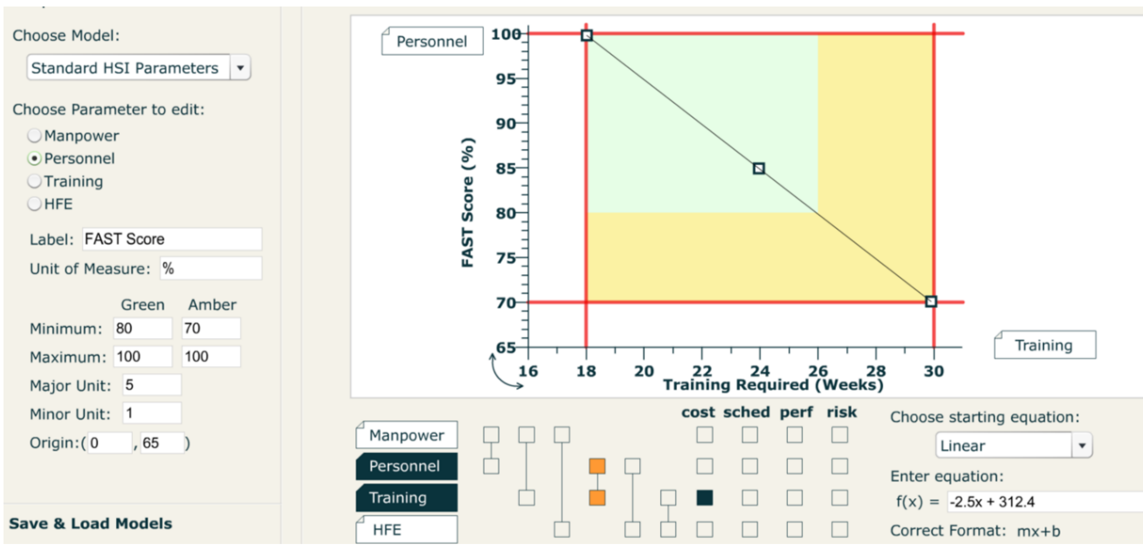

Figure 4. Personnel vs. Training relationship based on a user-defined linear model in the TST. Source: HSI Trade Space Tool (n.d).

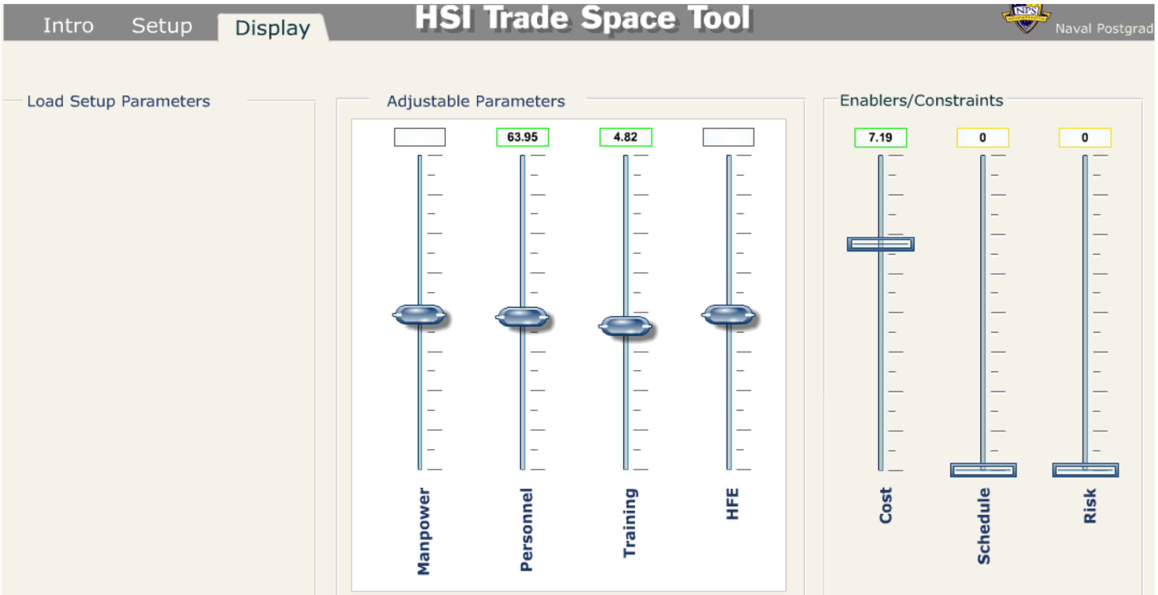

Figure 5. Personnel vs. Training values based on interactive slider positions and user-defined decision variable relationships. Source: HSI Trade Space Tool (n.d.).

C. SUMMARY

HSI is a contained system within SE, and SE is a contained system within the DAS (Figure 3). The DAS uses SE to optimize TSP and minimize cost, and SE likewise requires HSI to do the same. One method for optimizing HSI relates domain inputs to system outputs via the MBHSI standardized process. The resulting output of the MBHSI process can then inform the inputs to an MP. The MP constructed in Chapter IV relies on MBHSI and GSPT to provide data that is used to optimize TSP and minimize the cost of subjects in an aircraft simulator experiment.

III. GSPT AND MBHSI PRIMER

GSPT provides the underlying theory that MBHSI utilizes to quantify the HSI domain data; concurrently, MBHSI models HSI domain resources in terms of GSPT constructs. These domain resources can then be related to system-level performance. The MP crafted for HSI in this thesis uses the theoretical relationships provided by GSPT and empirical data measured in Taranto's (2020) MBHSI study to elaborate a formulation that relates three HSI domains.

A. GENERAL SYSTEMS PERFORMANCE THEORY

A chronic challenge for HSI has been identifying an underlying theory that unifies HSI domains with each other and with TSP (Booher, 2003, p. 234; Taranto, 2020). Creswell (2018) describes scientific theory as relating independent variables to dependent variables and providing the "why" and "how" for the relationships. Zimring (2019) suggests, however, that no scientific theory is useful without predictive capabilities. Moreover, Novella (2013) maintains that theory must be testable, falsifiable, and predictive. As a candidate theory for HSI, GSPT fulfills all of these requirements. GSPT provides a method to model "systems, tasks, and their interface using an abstraction that focuses on performance" (output) and resources (input) (Kondraske, 2011, p. 238). GSPT also provides the "input/output" data needed to formulate MPs: decision variables, constraints, and objective functions.

1. GSPT Relevance for DOD

The DOD's HSI Task Force identified the need for a framework to organize human performance in 2009 (Defense Safety Oversight Council, 2010, p. 2). In 2010, the Defense Safety Oversight Council (DSOC) tasked the HSI Task Force with "improv[ing] safety and reduc[ing] mishaps" across the DOD using HSI (p. 1). This tasking resulted in a workshop involving 25 individuals from 18 organizations, all of whom had expertise in human performance or HSI. The workshop evaluation and conclusions "converged on recommending exploration of General Systems Performance Theory . . . to address a host of problems faced by the DOD in making the best use of human performance advances in today's dynamic environment" (p. 2). The HSI Task Force concluded, "There is strong consensus that GSPT and NCRA show great promise as a very capable, evidence-based framework with multiple military applications" (p. 3). It continued by identifying potential GSPT applicability in multiple HSI domains, including GSPT's ability to optimize domains while reducing costs and mishaps (p. 1).

Despite the DSOC's recommendations, GSPT was not aggressively pursued in the DOD until Taranto's (2020) dissertation work. As of 2021, early GSPT efforts have also begun in the DOD with the Uniformed Services University of the Health Sciences, the USAF's 711th Human Performance Wing, the USAF's Test Pilot School, and the U.S. Space Force. These research efforts will continue the work of Kondraske—the creator of GSPT—and others who have utilized GSPT in various applications. A more complete listing of GSPT efforts can be found in "General Systems Performance Theory: Annotated Bibliography–External Sources" (Kondraske, 2019). This annotated bibliography is a list of dozens of authors, other than Kondraske, who have utilized GSPT or GSPT derivatives for research work.

2. Overview

Kondraske (2011) created GSPT "to obtain a quantitative understanding of the interface of human systems to tasks" (p. 235). He sought a generalized approach to performance understanding and measurement that could cope with complex systems. Moreover, Kondraske (2006) affirmed that humans are complex systems, and GSPT addresses this complexity from an engineering perspective.

Kondraske created and combined multiple interdisciplinary concepts to develop GSPT over the course of several decades. He used a systems engineering approach; measured and quantified performance with a unique method; utilized threshold-based (as opposed to correlation-based) relationships between independent and dependent variables; considered hierarchies of performance; created a comprehensive taxonomy of human performance with a monadological approach; considered a multi-dimensional approach to human performance quantification; created a task-analysis and performance-prediction methodology (the "math" behind GSPT); and applied economic theory to resources. Figure

6 shows some of these concepts. What follows are the basics of GSPT necessary to understand the work in this thesis. We make several simplifications of GSPT for the sake of clarity. The examples used relate to Taranto's (2020) MBHSI experiment, and Section C of this chapter demonstrates multiple visualizations of GSPT to explain key concepts. For an in-depth explanation of GSPT, see Kondraske's (2011) comprehensive article.

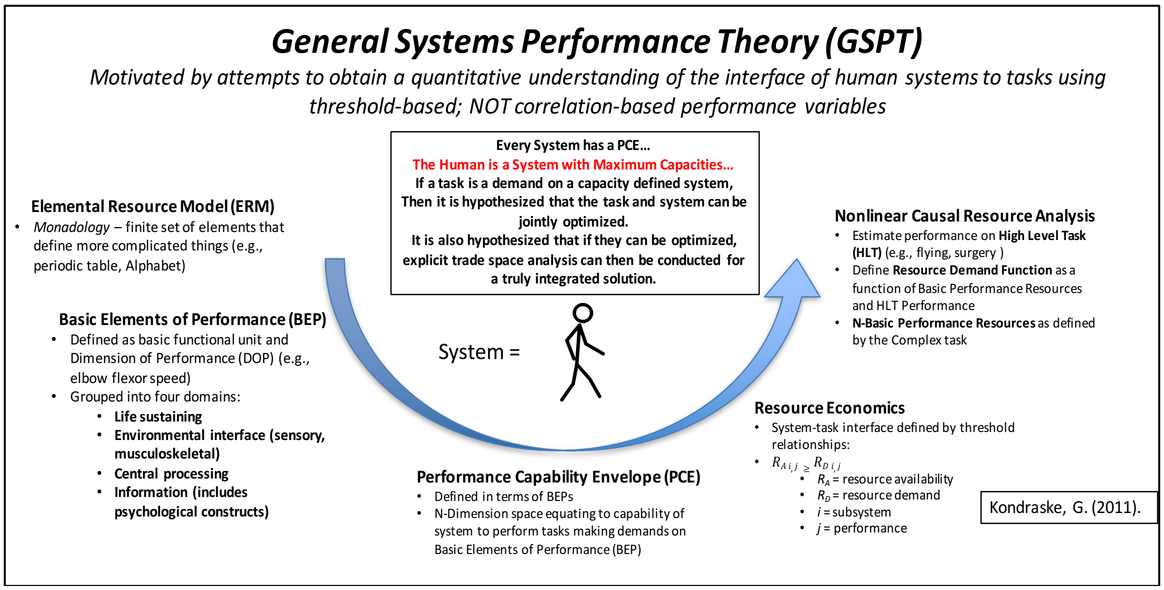

Figure 6. GSPT overview. Source: Taranto (2020, p. 40).

3. GSPT Fundamentals

GSPT relates an individual's basic "lower level" knowledge, skills, and abilities to "higher level" overall performance. More specifically, GSPT relates basic performance resources (BPRs) with high-level task performance (HLTp). Examples of BPRs include skills such as limb coordination, spatial awareness, and math processing ability. High-level task (HLT) examples include flying an aircraft, firing a weapon at a target, or piloting a boat in a friendly harbor. A key concept of GSPT is that it recharacterizes human capacities as input resources (Kondraske, 2011, p. 239). Thus, each human possesses sets of BPRs. That is, the human's performance resources are defined at various levels of hierarchy such that relevant sets of BPRs combine to accomplish an HLT. Furthermore, each BPR contributes to a multidimensional performance envelope that defines the overall capacity of a single subject.

Next, GSPT asserts that the principles of resource economics can model an individual's performance, based on supply and demand (Kondraske, 2011, p. 240). When an HLT places resource demands on an individual, the individual's BPR availability (i.e., resource availability, or R_A) must then exceed the task's BPR demands (i.e., resource demand, or R_D) for successful task performance. In other words, the individual's resources must be available in sufficient quantity to satisfy the resource demands presented by the task. Thus, a threshold relationship between the HLT and R_A exists such that a particular BPR (or multiple BPRs) limits HLTp. In other words, the individual's R_A is less than the task's R_D for that BPR. Nonlinear curves model this threshold over the values of HLTp (Figures 8 and 9). Adding more of a limiting resource will improve HLTp until another limiting BPR is encountered for a particular task (HLT) and a specified performance target (HLTp) as seen in Figures 18 and 19. This threshold-based approach is distinct from correlation-based relationships typical when using regression analysis.

The following figures illustrate the above concepts for a specific performance relationship. Figure 7 shows a BPR scatterplot wherein each point illustrates an individual's capacity on a BPR and their corresponding HLTp. For example, a point might represent the single BPR of reaction speed and the subject's observed resultant HLTp. Figure 8 depicts the resource demand function (RDF) curve as a near-lower boundary of the BPR scatterplot. This "threshold" defines the minimum BPR or R_D needed to attain a specific HLTp. Figure 9 shows multiple BPRs and RDFs predicting one individual's performance. Note that these graphs indicate movement from the y-axis to the RDF and then down to the x-axis, which is opposite the typical direction considered with independent and dependent variables. Because multiple BPRs are required to achieve an HLT, these graphs show which BPRs may limit HLTp. Table 1 summarizes the key GSPT abbreviations referenced in the rest of this thesis.

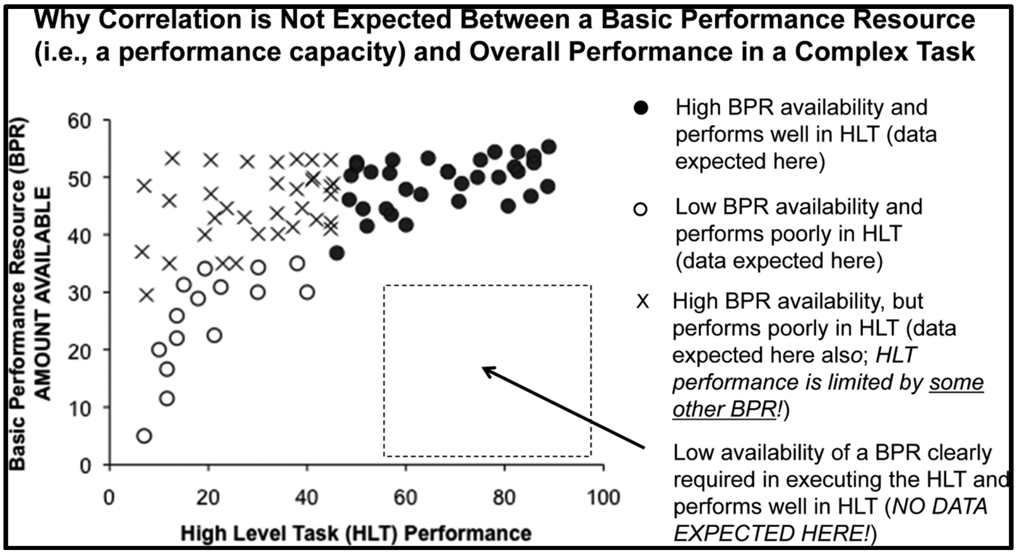

Figure 7. BPR scatterplot. Source: Kondraske (2011, p. 249).

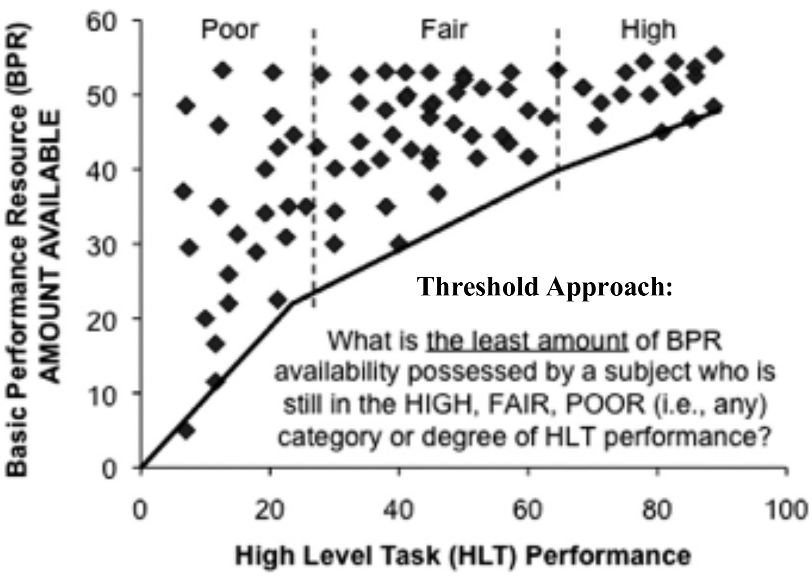

Figure 8. BPR scatterplot with a threshold resource demand function. Source: Adapted from Kondraske (2011, p. 250).

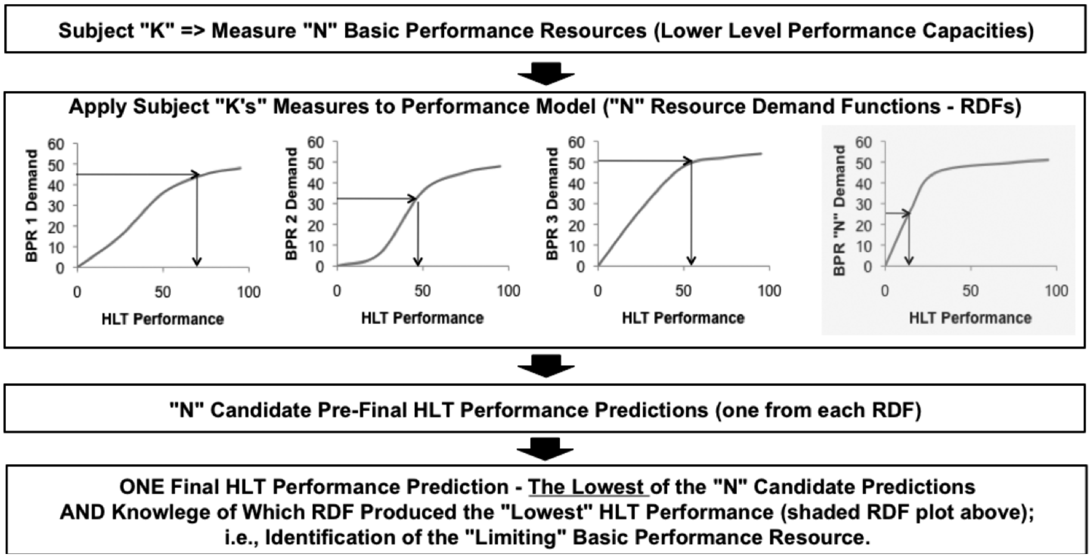

Figure 9. Summary of the GSPT forecast process.
Source: Kondraske (2011, p. 251).

Table 1. Important GSPT acronyms and their meanings.
Adapted from Kondraske (2011).

Abbreviation	Long Form	Meaning	Examples
BPR	Basic Performance Resource	Lower-level human capacities required to complete a higher-level task	Spatial awareness, limb coordination, reaction speed
HLT	High-Level Task	Tasks supported by more basic tasks (i.e., BPRs)	Flying an instrument approach in an aircraft simulator
HLTp	High-Level Task Performance	Quantified measurement of a given HLT	An instrument approach score based on deviation from the ideal airspeed, glidepath, and glideslope
PCE	Personal Capacity Envelope	A multi-dimensional performance space with each dimension representing a unique BPR that contributes to quantifying the HLTp. Each PCE is unique to an individual.	See Kondraske (2011), p. 240, Figure 4
R_A	Resource Availability	An individual's BPR capacity	Figure 15
R_D	Resource Demand	The minimum BPR quantity (or quantities) required to achieve a given HLTp value	Figures 17 and 22
RDF	Resource Demand Function	The lower bound BPR vs. HLTp scatterplots (i.e., threshold). The RDF relates the HLTp with the R_D for a given BPR.	Figures 17

B. MODEL-BASED HUMAN SYSTEMS INTEGRATION

1. Motivation

Tvaryanas (2010) and Taranto (2020) outline multiple challenges in the current practice of HSI. The authors discuss how HSI lacks a standardized body of knowledge, practice standards, efficacious and accepted methods and metrics, connections between HSI means and total system performance ends, standardized semantics, and policy mandates. According to Tvaryanas (2010) and Taranto (2020), these deficiencies affect all stakeholders but, most concerningly, the end users in the domain of consequence. The USAF Scientific Advisory Board have voiced similar concerns, stating "over the past 20 years, the capabilities and expertise of the USAF to perform the critical function of HSI have become insufficient" and recommending re-energizing "the emphasis on Human Systems Integration throughout a weapon system's life cycle" (U.S. Air Force Scientific Advisory Board, 2012, p. viii). HSI challenges were likewise highlighted in 2019 during the DOD's annual HFE Technical Advisory Group meeting. The HSI capability gap panel identified five HSI shortcomings: the body of knowledge, TTAMs, HSI practice standards, workforce development, and policy (DOD HFE Technical Advisory Group, 2019). Indeed, although manpower, personnel, and training are three core HSI domains, there is no pipeline or accepted training regimen for new ascensions into HSI, no continuing education programs, and no cadre of trained mentors.

Taranto (2020), thus begins his dissertation by addressing some of these deficiencies:

> HSI lacks a generally accepted unifying theoretical perspective that joins HSI domain resources in terms of total systems performance (TSP). The warfighter, HSI, SE, and the DOD would benefit from a theoretical perspective that bridges domain considerations with TSP in terms of HSI. (p. 7)

His consolidated thesis statement asserts that "GSPT/NCRA can reliably forecast TSP as a function of HSI domain resources" (p.7). To substantiate his thesis statement with MBHSI, Taranto performed a functional decomposition of the field of HSI. To guide his development of MBHSI and satisfy HSI's containing system requirements, Taranto defined six consecutive functional requirements (FRs) for MBHSI (see Figure 10). With this initial roadmap, Taranto set about creating MBHSI.

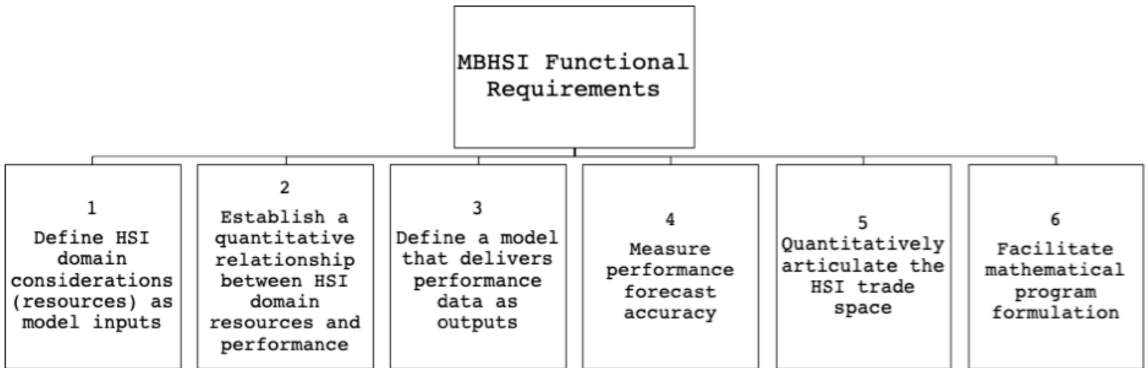

Figure 10. MBHSI Functional Requirements. Source: Taranto (2020, p. 18).

2. Overview

In order to achieve the DOD's stated objective of HSI—maximizing TSP and minimizing cost—Taranto proposed MBHSI as a standardized, theoretically based, empirical modeling process designed to work within the DAS. He defined MBHSI as follows:

> an essential, model-based, and integrative process that reliably addresses complexity in terms of resource economics while enabling the SE practice. It applies GSPT and NCRA to model and forecast the quantitative relationships between HSI domain resources and system-level performance, targeting the chronic HSI trade space problem and the original objective of HSI, optimization. Finally, it seeks to communicate its engineering and program management value in engineering terms. (p. 56)

MBHSI's output is thus the quantitative relationship between HSI domain resources (individual human capacities) and system performance. Recall the relationship between the MBHSI, OR, and MBSE cogs depicted in Figure 1. Taranto's experiment demonstrated the first cog. This thesis takes the output of MBHSI (i.e., the sixth functional requirement from Figure 10) and formulates mathematical programs to demonstrate how MBHSI might optimize TSP and minimize cost, thus enabling the second cog in Figure 1 and improving the capacity of HSI to enable MBSE/SE.

Taranto recharacterized the HSI domains in terms of GSPT, defining the domains with equivalent terms and comparable units to enable trades between them. Table 2 summarizes this recharacterization. See the *Defense Acquisition Guidebook* for the original definitions of the seven DOD acknowledged HSI domains (DAU, n.d.).

Table 2. HSI domains recharacterized in GSPT terms.
Source: Adapted from Taranto (2020).

HSI Domain	MBHSI Recharacterization	MBHSI Explanation
Personnel	R_A Current resource availability	Represents an individual's initial set of BPRs (i.e., their PCE) including both malleable and non-malleable BPRs.
Training	R_A increase and PCE expansion Potential resource availability	A user-population can train to malleable BPRs and thus R_A can be increased and/or maintained.
Human Factors Engineering (HFE)	R_D expansion or compression and thus RDF changes; introduction of new/different R_A and BPRs Potential resource efficiencies or drains based on HFE design	HFE interventions redefine the value and types of required BPRs based on a given HLTp. HFE interventions also redefine the RDF shape. HFE interventions can be targeted to relieve the most limiting BPRs for an HLT and given HLTp.
Manpower	$\sum_i PCE$ All resources available from all the subjects in a cohort; cohort R_A	The summed volume of all the individual PCEs in a given DOD cohort (i.e., specialties, organizations, commands, or teams).
Force Protection/ Survivability	Minimize acute R_A loss; Minimize acute R_D increase	The margins from the edges of the RDFs (i.e., margin = $R_A - R_D$ or R_A/R_D) represent this domain, especially for limiting BPRs and during critical phases of a task.
Occupational Health	Maintain long-term R_A; decrease long-term R_D effects	Occupational Health is represented by acute, chronic, and longitudinal demands, prevention, diagnoses, and/or rehabilitation involving R_D or R_A. The R_D and HLT's environment, preparation, impact, and recovery must be considered. The R_A/R_D ratio must be considered, along with non-malleable human requirements (e.g., oxygen, hydration, nutrition, environmentals, sleep, etc.).
Safety	Minimize acute R_A loss Minimize acute R_D increase	Safety shares many aspects of Occupational Health but is more acute and "tactical" in nature. Safety involves R_A and R_D. Safety involves the R_A/R_D relationship and fluctuating HLTps that exceed the individual's PCE.
Habitability	R_A and PCE regeneration and maintenance	Acute, chronic, and longitudinal PCE regeneration and maintenance involving R_A and R_D Increase or decrease the ambient, non-tactical, R_D and R_A to regenerate, increase, or maintain the PCE.

3. The Inaugural MBHSI Experiment

a. Context

Taranto's (2020) MBHSI dissertation sought to determine if HSI can be reframed in terms of GSPT and NCRA to demonstrate improved complex system attribute forecast accuracy and increased system value. As stated previously, Taranto's condensed thesis statement contends that "GSPT/NCRA can reliably forecast TSP as a function of HSI domain resources" (p. 7). Finally, he lists his alternate hypothesis as follows:

> **H_A:** HSI can be reframed in terms of GSPT and NCRA to improve adherence with containing system requirements (Condition B: Theoretical). (p. 65)

Taranto's experiment showed that by using GSPT concepts, a quantified high-level task (HLT) can be related to lower-level tasks (BPRs), and an individual's set of BPRs can predict HLTp. Likewise, a given HLTp value can predict the minimum levels of BPRs (R_D) to achieve that HLTp. Taranto then shows that these constructs can be characterized as human capacities (i.e., HSI domain resources), which should reliably forecast TSP.

b. Methods

Taranto (2020) chose a simulated aircraft instrument landing system approach for his HLT. He studied 64 heterogenous subjects, excluding those younger than 18, non-federal government employees, and subjects with experience flying aircraft or gaming. First, each subject's performance on 19 BPRs was measured (17 BPRs were used for subsequent analysis). The BPRs included relevant basic tasks described by O*NET (n.d.) and Fleishman's (1992) *Handbook of Human Abilities*, such as reaction speed, perceptual integration capacity, and limb coordination speed/accuracy (Taranto, 2020). Based on a literature review, analyzing the flying task, and referencing O*NET (n.d.), Taranto had postulated that these BPRs were relevant to the HLT of flying a simulated instrument approach (Table 3). For more information on the BPRs, see Taranto (2020, Appendix G).

Table 3. BPRs measured in Taranto's MBHSI experiment. Adapted from Taranto (2020).

BPR Number	BPR Name (units)
1	Multi-Limb Coordination (Speed*Accuracy)
2	Multi-Limb Coordination Accuracy (exp-0.065)
3	Multi-Limb Coordination Speed (cm/sec)
4	Visual Motion Prediction Accuracy (1/score)
5	Visual Motor Tracking Accuracy (score/30sec)
6	Multi-Choice Reaction Speed (1/score)
7	Automated Neuropsychological Assessment Metrics (ANAM) Math Speed (1/(60,000/speed in mil sec))
8	ANAM Math Accuracy (% correct)
9	ANAM Math Throughput (Speed*Accuracy)
10	ANAM Spatial Orientation Speed (1/(60,000/speed in mil sec))
11	ANAM Spatial Orientation Accuracy (% correct)
12	ANAM Spatial Orientation Throughput (Speed*Accuracy)
13	ANAM Switching Speed (1/(60,000/speed in mil sec))
14	ANAM Switching Accuracy (% correct)
15	ANAM Switching Throughput (Speed*Accuracy)
16	Perceptual Integration Capacity Concealed Words (% correct)
17	Perceptual Integration Capacity Snowy Pictures (% correct)

Next, each subject was given a basic orientation in flying a simulated instrument approach in the aircraft simulator, followed by a practice run. The simulator software then scored the second flight based on FAA criteria of airspeed, glidepath, and glideslope deviation from the ideal. Subjects were then categorized in four different cohorts: the first was no intervention, the second was video-based training, and the third and fourth automated an aspect of the flying task (Table 4). Each individual then had the third and final flight scored (Taranto, 2020).

c. Results

Taranto's (2020) experiment resulted in 5,850 data points captured in an Excel spreadsheet. The raw data, relevant to this thesis, included 17 BPR scores and an HLTp for each of the 64 individuals. Taranto then fit RDFs to 17 BPRs using novel R code. The vast majority of resultant scatterplots and RDFs demonstrated solid GSPT characteristics as described by Kondraske (2011).

Taranto analyzed the data from several perspectives, but one of the most striking findings was agreement between predicted HLTp (based on the subject's 17 R_A's) and actual HLTp. The agreement was within 2.5%. A few additional relevant results are listed in Table 4, which shows that the third flight resulted in increased median scores for each group, with the HFE groups showing substantial increases in HLTp.

Table 4. Median scores for each group. Adapted from Taranto (2020).

Track	# of Subjects	Second Flight Median Score	Intervention	Third Flight Median Score
A: Control	40	272	None	706
B: Training group	10	91	Professional video-based training	465
C.1: HFE group 1 (Course automated)	7	267	Course automated	21,813
C.2: HFE group 2 (Glideslope automated)	7	2,643	Glideslope automated	44,183

d. Inferences

The results of Taranto's (2020) study suggest that GSPT can accurately forecast TSP as a function of BPRs and human capacities (i.e., HSI domain resources). The quantified relationships between the BPRs and HLTp in the form of the RDFs demonstrated the model's applicability to the human system. Furthermore, the experiment achieved the six functional requirements of MBHSI and thus provided data amenable to

MPs, as shown in Figure 11. Taranto (2020) thus made the following suggestion for the first follow-on study to his work:

> The critical next step for MBHSI is engagement with OR [operations research] experts to explore a spectrum of HSI decision problems and formulate them. This is the operationalization of MBHSI. This dissertation demonstrated that obtaining reliable OR model variable values is possible. Exploration of LP [linear programming], nonlinear programming, multiple objective functions, minimum cost network flow, efficient frontiers, and goal programming represent but a small sample of proven OR methodologies that may be possible with MBHSI. (p. 199)

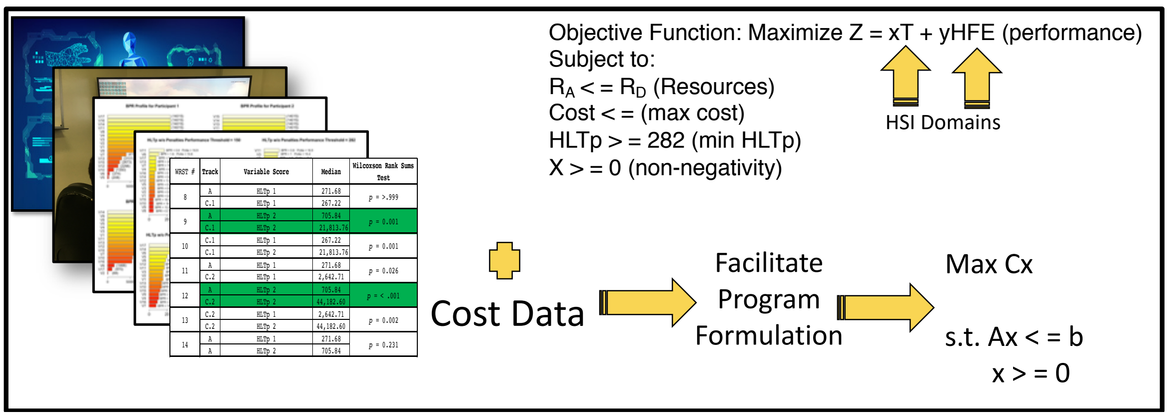

Figure 11. MBHSI's mathematical program formulation concept of operations. Source: Taranto (2020, p. 184).

4. Summary

Taranto (2020) sought a "unifying theoretical perspective that joins HSI domain resources in terms of TSP" (p. 7) to satisfy HSI's containing system requirements (see Figure 3). MBHSI utilizes GSPT to provide this theoretical perspective. Together, MBHSI and GSPT outline the theoretical and practical constructs to quantify the human and thus the HSI domain resources. This data then informs the containing system of SE through optimized MPs. The following section ties together the key elements of GSPT and MBHSI from multiple visual perspectives.

C. VISUALIZING GSPT AND MBHSI

The works of Kondraske (2011) and Taranto (2020) present useful information, knowledge, and metrics, but they offer limited graphical depictions of their concepts. This section augments their concepts and helps the reader visualize the data used for the MP formulation in the next chapter. Figure 12 demonstrates the conceptual relationships between the human, the system, the task, GSPT, HSI, MBHSI, and this work's MPs. Figure 13 graphically depicts the data provided by MBHSI and modeled with the optimization formulation of this thesis. The circles at the top of Figure 13 represent different BPRs relevant to the task. Each individual has different amounts of those BPRs (i.e., their R_A profile). The individual together with the technical system then bring their R_A profile to bear on a task, which results in an HLTp. The conceptual "locations" of the HSI domains of interest are illustrated along the right side of the image.

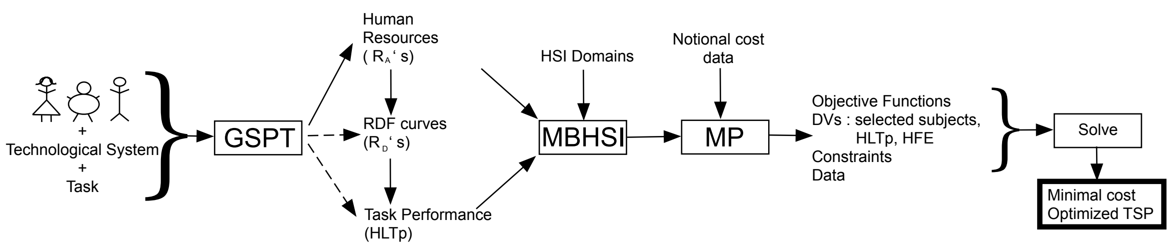

Figure 12. Graphical relationships between the human, GSPT, HSI domains, MBHSI, and MPs

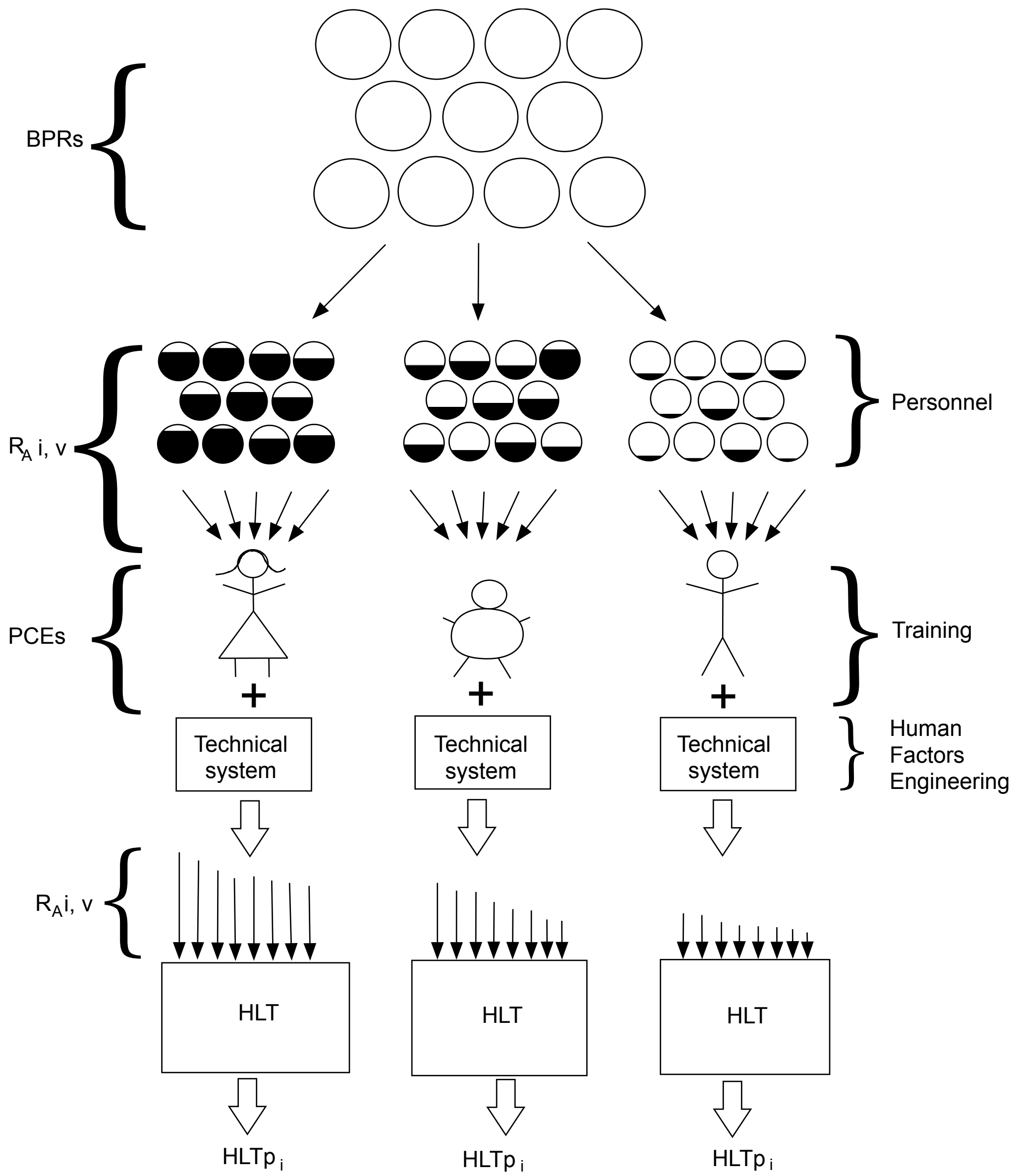

Figure 13. A visualization of MBHSI amenable to MP formulation

1. The Basic GSPT Scatterplot

A single GSPT scatterplot provides a wealth of information but is just one piece of the larger picture. Figure 14 shows multiple datapoints in grey with select datapoints in black, labeled 1 through 5. Each datapoint represents a subject's score on the plot's BPR, which is "spatial awareness" in this case. The x-axis of each datapoint corresponds with the score on the HLT. Thus, Subject 5 has an HLTp of 100 and an R_A of ~21. The units and values of each BPR can vary, but for simplicity, these graphs and this thesis utilize standardized scores from 0 to 100 and exclude units. The RDF curve is a lower percentile function constrained to be nondecreasing. It is often referred to as the "threshold curve." The threshold curve relates any given HLTp value to the R_A required to achieve that HLTp. For example, in order to score an HLTp of 100, one must have at least an R_A of 20.

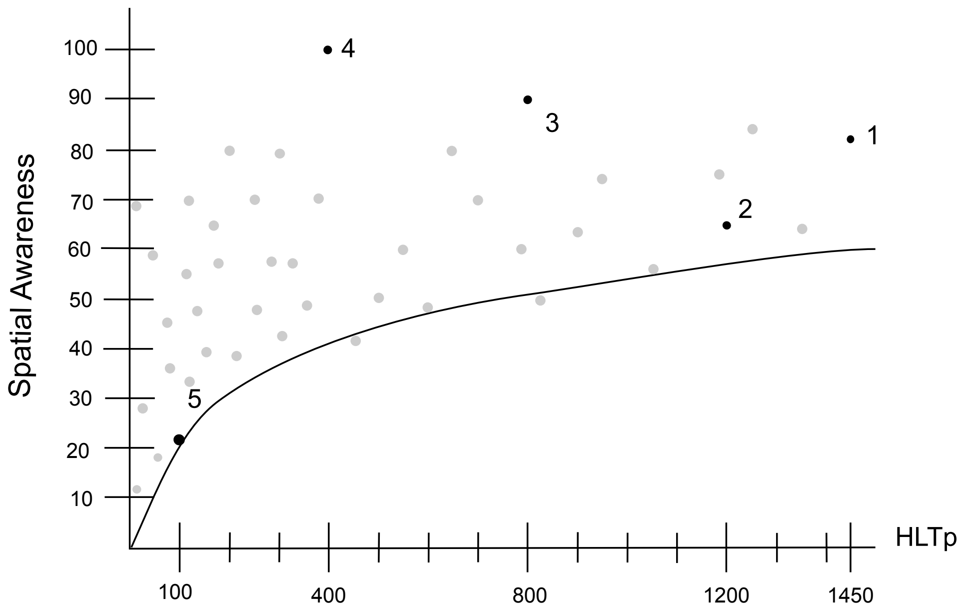

Figure 14. Basic GSPT scatterplot

Figure 15 demonstrates a more comprehensive way of visualizing GSPT models. Here, a vertical orientation displays three BPRs. Note, however, that a real-world experiment would likely measure more BPRs (Taranto utilized 17). This vertical alignment allows intuitive visualization of limiting BPRs and explains why a subject is limited to a specific HLTp score (assuming the appropriate number and type of BPRs are tested). For example, Subject 4 scored high on both the spatial awareness and limb coordination BPRs, but the subject's reaction speed clearly limited the HLTp from exceeding 400 on the x-axis. Similarly, Subject 2 scored lower than Subject 4 on the first two BPRs but higher than Subject 4 on reaction speed, thus achieving a higher HLTp.

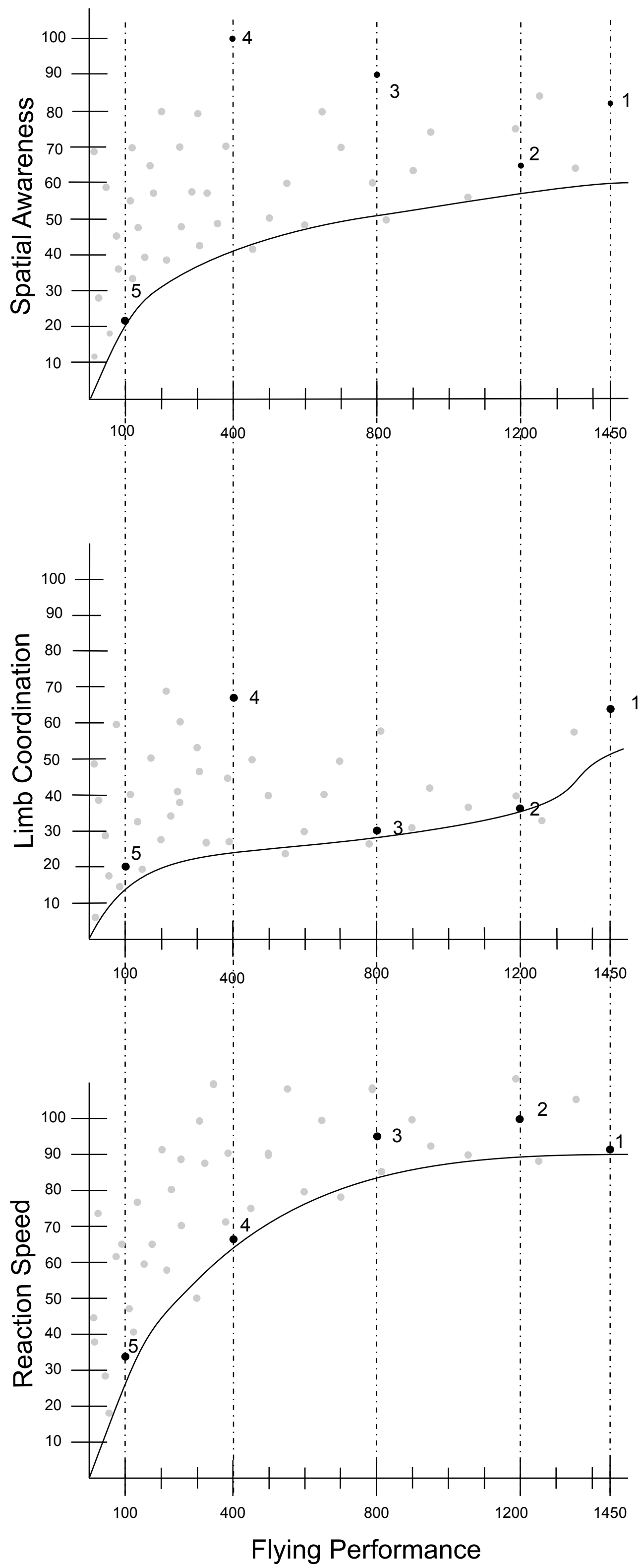

Figure 15. Vertically aligned GSPT scatterplots for intuitive interpretation

2. Axes

The horizontal axis on GSPT scatterplots represents the HLTp values. Designating HLTp as an independent variable in GSPT may seem counterintuitive given that the subject's R_A (BPR values) ultimately determines the HLTp. Kondraske uses this orientation because the HLTp is typically the known quantity from a systems perspective (DSOC, 2010, p. 7). That is, systems often know the required HLTp and then seek to determine the required resources to achieve that level of performance.

The vertical axis represents a single BPR's values. The values can be discrete or continuous based on the BPR. The units and scales of BPRs are typically variable; however, they are all standardized on a continuous scale of 0–100 in this thesis. This standardization includes the experimental BPR data from Taranto (2020) later in this thesis.

3. Datapoints

As discussed earlier, each point on the GSPT scatterplots represents a single subject's HLTp vs. BPR score (or R_A). Notably, vertically aligned points may be confusing to interpret. In Figure 16, individuals aligned vertically with Subject G all achieved the same HLTp, but they each scored differently on the BPR. Subject I has an excess of the BPR, and her performance is not limited by this BPR, while Subject E's HLTp is actually limited by this BPR (as can be inferred by his proximity to the threshold curve). Subject I's HLTp is limited by another BPR where she would be located much closer to that BPR's threshold curve. Subject I's situation is thus analogous to Subject 4 in Figure 15. Subject 4 has an excess of Spatial Awareness, but another BPR, Reaction Speed, limits her HLTp.

Points horizontally aligned on a single BPR scatterplot can likewise be confusing. Subject B had a low HLTp whereas Subject L scored a much higher HLTp. Another BPR limited subject B's HLTp, but Subject L's HLTp may have been limited by this BPR as evidenced by his proximity to the RDF.

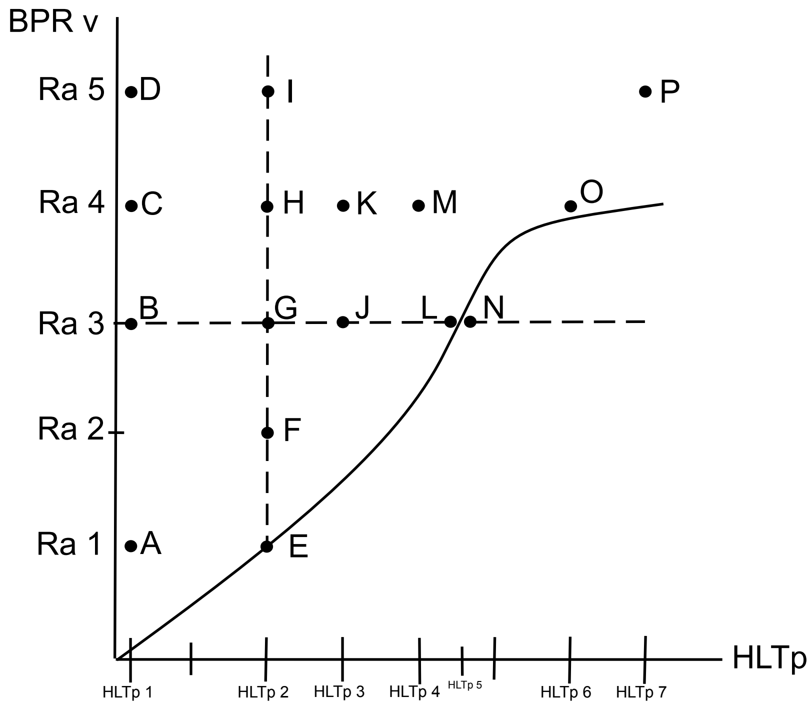

Figure 16. Relationships between datapoint locations

4. Resource Demand Function Curve Variations

The RDFs can display different characteristics. Figure 17 shows five theoretical RDF curves. Curve A illustrates that a large amount of R_A is required to score any given HLTp above some small value. Curve B is a "classic" curve that both Kondraske (2011) and Taranto (2020) have achieved experimentally. It shows that the amount of BPR required for a given HLTp increases approximately linearly until the curve flattens. Thus, adding BPR capacity beyond a certain point will not increase the HLTp. Curves C and D demonstrate nonlinear changes with changing HLTp values. Curve E is the opposite of Curve A, whereby a small proportion of BPR enables large HLTp values.

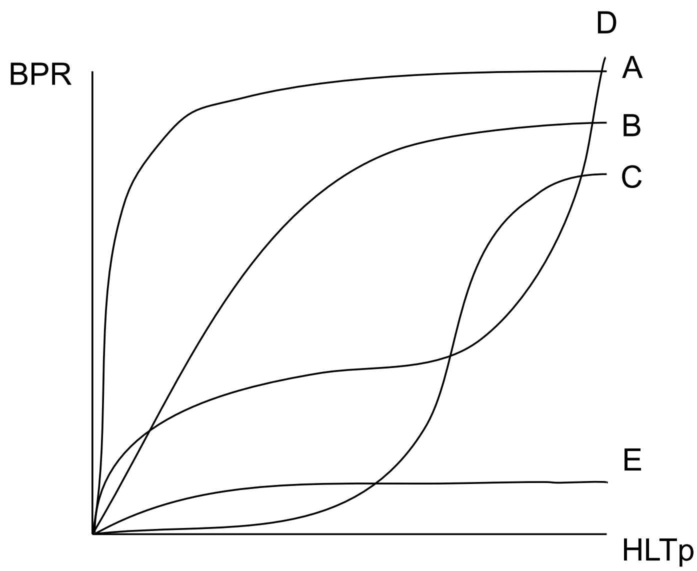

Figure 17. Different types of RDFs

5. The Personnel, Training, and HFE Domains in GSPT Models

There are unique ways to visualize each HSI domain recharacterized in MBHSI terms (Table 2). The MP in this thesis deals with the personnel, training, and HFE domains. Personnel can be quantified and visualized by considering a subject's PCE. In Figure 15, this can be visualized as a weighted sum of a particular subject's R_A's, their predicted HLTp, and a desired HLTp.

Training ultimately increases an individual's R_A values. Limiting BPRs are those with R_A values very near the RDFs, thus limiting the subject's HLTp. Figures 18 and 19 show multiple BPRs including the most limiting BPRs for a single subject. In Figure 18, the horizontal arrows from the subject to the RDF threshold curve for each BPR demonstrate the HLTp that is predicted based on the subject's individual R_A values. The subject would thus need to train on BPR 5, 11, 14, and 7 to achieve the "HLTp Desired" score. Of note, the subject's BPR 15 value does not have much margin but appears sufficient to enable the "HLTp Desired" score. The BPR 8 and 3 scores are also sufficient.

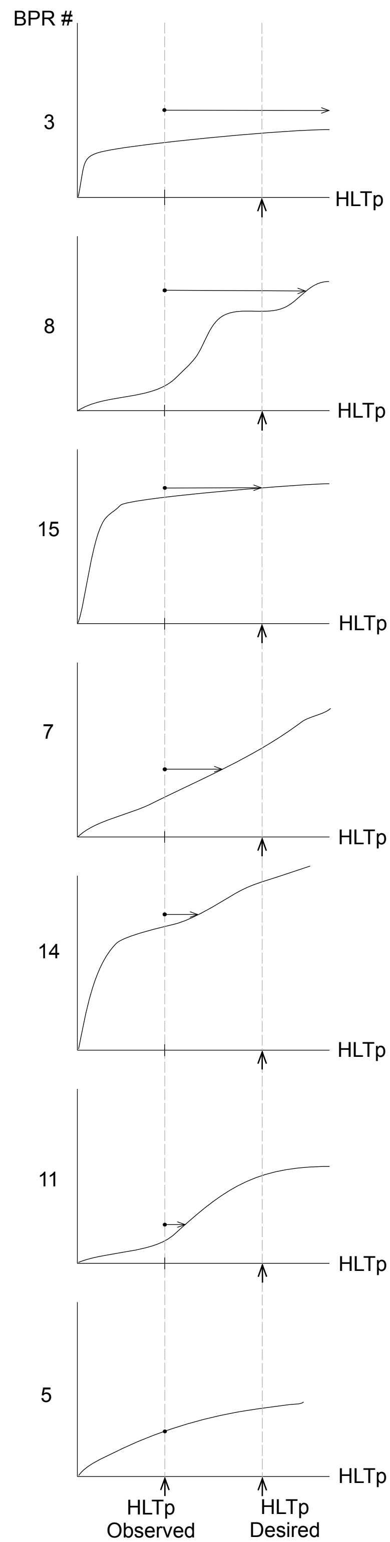

Figure 18. Limiting and non-limiting BPRs when striving for a performance score of "HLTp Desired"

Figure 19 illustrates the conceptual "movement" of a subject during training. Each time step shows improvements in R_A (and assumes these particular BPRs have no BPR-to-BPR interactions). After the BPR 5 score and thus HLTp first increases, at time t = 2, the HLTp is then limited by both BPR 5 and 2. Hence, both must then be trained until time t = 3. At this point, BPR 5, 2, and 13 must be trained (increased) to obtain the desired HLTp at t = 4.

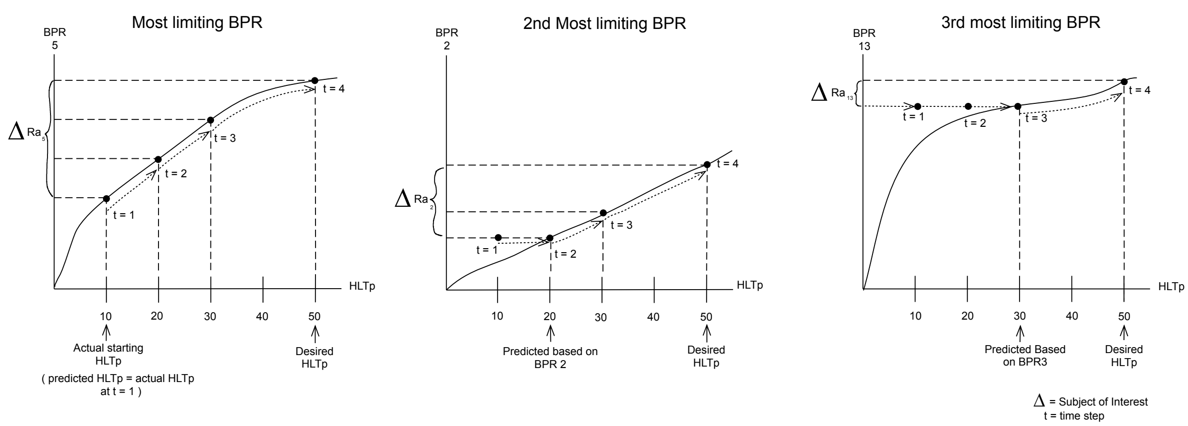

Figure 19. Training visualized across three BPRs

The RDF curves reflect changes in HFE. For example, when a new feature such as automation is added to a system, the desired outcome is higher system performance and ease of use for the human operator. The top scatterplot and RDF in Figure 20 are the same as the top scatterplot and RDF in Figure 15. The top RDF is based on no HFE intervention. The lower RDF is flattened and reflects a change due to an HFE intervention. Thus, Subject 5, who initially scored an HLTp of 100, can now theoretically score an HLTp of greater than 800, assuming that no other BPRs are limiting him.

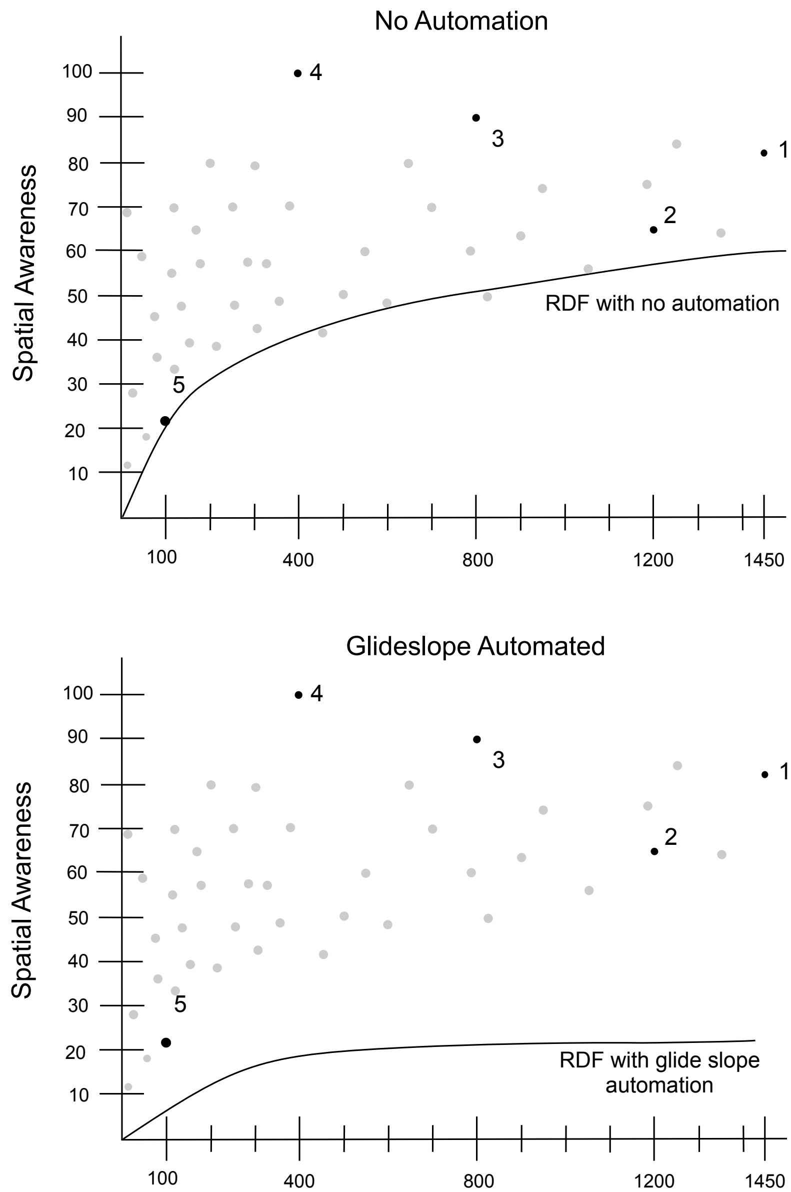

Figure 20. RDF changes with HFE interventions

The rest of the HSI domains—manpower, force protection/survivability, habitability, occupational health, and safety—each have their own GSPT visualizations as well. For example, in Figure 21, the "safety margin" for Subject B on this single BPR can be considered to be the Δ value between point A and B. Thus, Subject B's R_A can be degraded this Δ amount without decreasing the HLTp value.

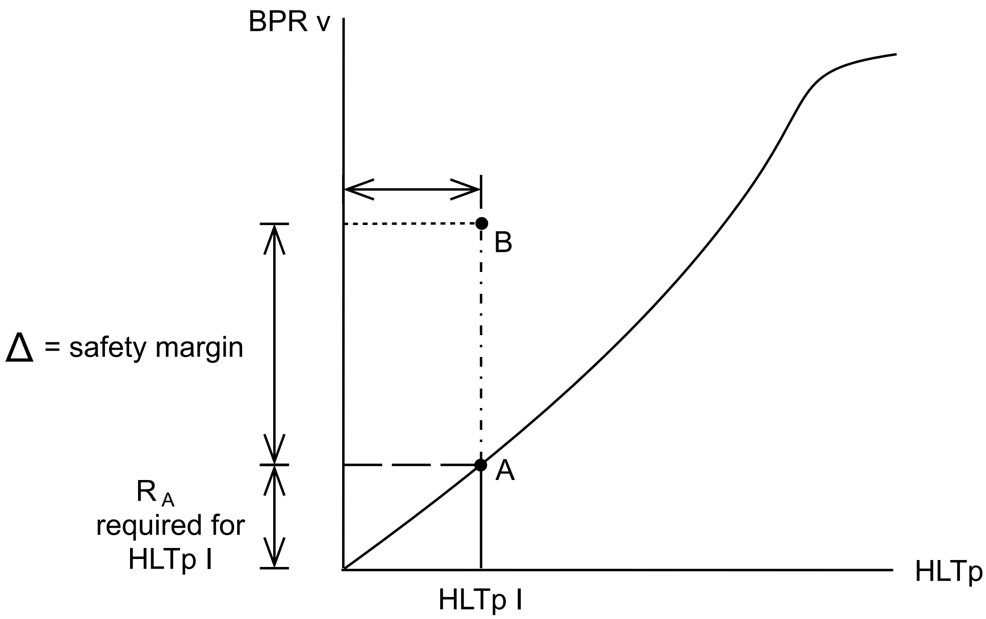

Figure 21. The Safety domain in GSPT

D. SUMMARY

GSPT provides a theory and means of quantifying human resources (i.e., HSI domain resources) and relating them to TSP. MBHSI recharacterizes HSI domains in terms of GSPT constructs. These GSPT constructs can be visualized as above to yield insight into systems of interest. Furthermore, MBHSI requires the underlying analytical relationships that GSPT provides in order to provide data amenable to MP formulation, as the Chapter IV will demonstrate.

IV. METHODS

The tangible result of this thesis is an optimization model that utilizes MBHSI output along with notional cost data to define the tradespace between three HSI domains. We developed the model in a stepwise fashion from concept to MP formulation to computer code. Our work leveraged knowledge of MBHSI and GSPT, MPs, stepwise-nonlinear handling of the RDF curves, and Julia and R code. The final product was a Mixed Integer Non-Linear Program (MINLP) that modeled three HSI domains, allowed for quantitative tractable domain trades, and accounted for variable costs, HFE configurations, RDFs, subject data, and HLTp values. The MINLP is presented in NPS standard format in Tables 6 - 10.

A. MODEL FORMULATION

1. Model Conceptual Design

The conceptual background for this model was straightforward: an optimal combination of HSI domain resources (in the form of human R_A) must combine to enable a system's desired performance. Figure 12 provides a broad overview of the concepts, and Figure 13 depicts HSI resource flow (via R_A) to illustrate the core concept. For example, resource-poor subjects (those with low R_A values and small PCEs) cost less to acquire but more to train. Resource-rich subjects, on the other hand, cost less to train but more to acquire. HFE can obviate many resources and thus the need for training or acquiring expensive subjects. However, HFE may require other or new resources and can be very expensive. The model must determine which subjects and, thus, which domain resources are required to attain a desired performance level (HLTp) at minimal cost (i.e., the goal of HSI).

2. Model Development, Assumptions, Simplifications, and Data

We developed the model using data from Taranto's (2020) MBHSI process and experimental results, along with various assumptions, simplifications, and stepwise refinements (Pidd, 2009). Furthermore, Taranto's data were used with knowledge of their limitations and the scope of the experimental setup. Table 5 outlines the key model assumptions and conventions.

Table 5. Model assumptions and simplifications/exposition

Item		Assumptions	Simplifications and Relevant Exposition
MBHSI Models	BPRs	• Taranto's experiment used an appropriate sampling of BPRs, in accordance with tenets of GSPT. • Costs assigned to BPR 4 were minimal due to concerns over BPR 4 scale, outliers, and reliability.*	• For tractability, the BPR (and thus R_A) values were standardized from 0 to 100 based on Taranto's data.* • BPRs shown to be most limiting at high performance were considered more expensive to train and acquire (see "cost data" below).
	Subjects	• All subjects gave their best effort at the BPRs and HLTp.	• This model utilized Taranto's subjects and their R_A's, but could have used randomly generated R_A's and different subjects. • A subject is defined by a PCE, a collection of R_A, that is used to predict their resulting HLTp and costs.

	RDFs	• HFE interventions resulted in 14 BPRs' RDFs that decreased, 1 that stayed the same, and 2 that increased (Table 11).
		  ○ Configuration 1: no automation
		  ○ Configuration 2: glidepath automation
		  ○ Configuration 3: glideslope automation
			• Calculated from the MBHSI experimental data via R code as stepwise-nonlinear segments.
			• Represents the 93% threshold for the experimental data. For the optimization model, the RDF curves enforce threshold constraints. Thus, no datapoints in the optimization model solutions will be below the curves.
			• Due to fewer datapoints at high HLTp, the RDFs have less resolution as the HLTp increases.

	HLTp		• When operationally selecting an HLTp value, a conservative measure means adding a safety margin/"buffer" to the desired value. For example, if the desired HLTp is 100, actually run the model for 110 for a 10% safety margin. This work did not utilize a safety margin, but was solved for an HLTp minimum value, and an HLTp average value that was 110% of the minimum value.

Item		Assumptions	Simplifications and Relevant Exposition
Cost Data	Personnel	• BPRs that were the most limiting for an HLTp of 5000 in Taranto's study were used to price out the personnel costs.* • BPRs that generally correspond to higher scores cost more. • Personnel costs were constant values.*	• Personnel costs are only a function of an individual's PCE. • Notional data were assigned as the cost per unit BPR for each BPR. • The cost to acquire an individual is the sum of all 17 R_A scores. • This model did not include time (as a decision variable) to attain/select personnel.
	Training	• BPRs that were the most limiting for an HLTp of 1500 in Taranto's study were used to price out the training costs.* • BPRs that generally correspond to higher scores cost more. • Training costs are constant values*	• Notional data were assigned as the cost per unit BPR for each BPR. • The cost to train an individual was broken down to the amount of training required per each BPR times the cost of that BPR. • Time (as a decision variable) to complete training was not included in this model.
	HFE	• A single cost was assigned to each HFE configuration.	• Experimental data on the two HFE configurations were limited by small numbers of subjects (Taranto, 2020); however, RDFs for HFE configurations were calculated as a conservative fraction of the baseline RDFs. • Time (as a decision variable) to incorporate the HFE intervention was not included in this model.
Domains	Personnel		
	Training	• BPR-to-BPR training effects were not considered.*	
	HFE	• No new BPRs were tested for or considered with Configuration 2 or 3.*	• RDF decreases were seen by Taranto (2020), but the cohorts that received HFE interventions were small (7 subjects in each intervention group). • RDF increases are plausible for some BPRs based on new HFE configurations.

*The following sub-sections further explain these bullets.

a. BPR Tractability

Taranto (2020) expressed his BPR data in units relevant to each BPR. Some had scores from 0.50 to 2.32 while others had scores from 0.50 to 1000. We standardized the BPR values on a scale of 0–100 for all BPRs, which eased interpretation and the assignment of cost scores in units of dollars per unit BPR.

BPR 4 is "Visual Motion Prediction Accuracy." It was scored on a scale of 1 to 1000 and had a median score of 31, with three scores of 1000. Thus, the vast majority of scores were clustered at the low range of the BPR scoring scale. This BPR was in the mid to lower range of the R_D profiles (Figure 22), and these three subjects who scored 1000 were not outliers elsewhere. Their HLTp values were on the order of the median score at 167, 297, and 105. Furthermore, according to Taranto (personal communication, August 2, 2021), BPR 4 appeared to have an element of chance involved that obstructed its utility as a useful BPR. In an attempt to prevent BPR 4 from over or under "pricing" these three subjects, costs assigned to BPR 4 were minimized to prevent unduly influencing the model. Thus, the cost value for this BPR was $.01/unit BPR for the Personnel and Training domains.

b. Training and Personnel Cost Data

Personnel and training cost data for the BPRs are notional, but based on the most limiting BPRs determined in Taranto's experiment (2020). The R_D profile at HLTp = 5000 (see Figure 22) determined the personnel cost data. The Pareto chart shows that at an HLTp of 5000, BPR 17 was the most limiting, followed by BPR 10 and 3. These BPR percentile values were scaled and then used to assign costs to the $Acquire_i$ parameter (Table 7) from as low as a cost of 25 [$/unit BPR] for BPR 2 to as high as 100 [$/unit BPR] for BPR 17. A similar process was used to determine the notional training cost data but using the R_D profile at HLTp = 1500 Pareto chart (see Figure 22). Thus, BPR 17 and 14 are the two most expensive BPRs to train for ($Training\_cost_v$), but BPR 14 is less expensive to acquire ($Acquire_i$).

The cost and amount of training required to achieve a given performance level can vary. Training for any given skill can impact and potentially improve another skill. For example, training for pull-ups would likely improve performance on a seated row. However, our model did not include these skill-to-skill or BPR-to-BPR interactions. BPRs and interventions were considered to be independent of each other. The cost of training for a particular skill also varies in vivo. For example, as a subject trains on a particular skill, scores can increase rapidly at the beginning of training but the rate of increase slows at performance plateaus. Thus, the cost-per-unit increase of a BPR would also change. However, we used constant training costs in the model. That being said, our approach can accommodate variable costs if available.

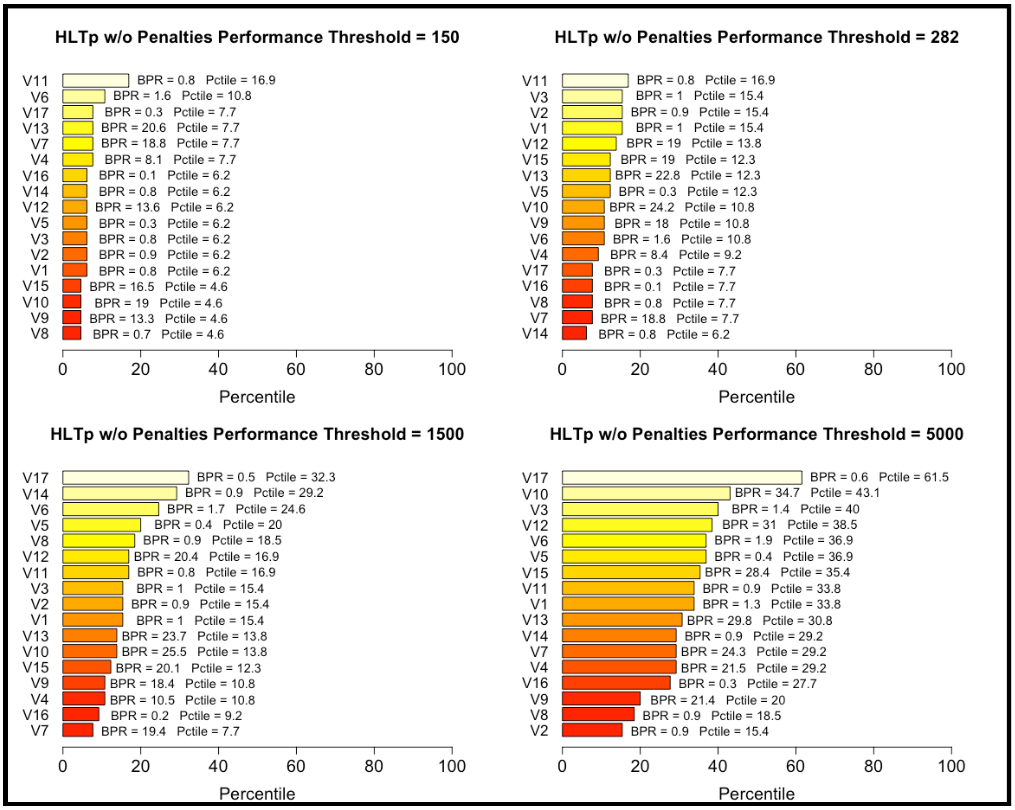

Figure 22. Sample R_D profiles at various HLTp scores.
Source: Taranto (2020, p. 120).

3. Optimization Formulation in the NPS Standard Format

Table 6. Index and set use

Index	Meaning	Potential Values	Further Explanation
i	Subjects	{1-a}	a = 64 subjects
v	Specific BPR (resources)	{1-b}	b = 17 BPRs
z	HFE Configuration	{1-c}	c = 3 total configurations—> z = 1 no automation z = 2 glidepath automation z = 3 glideslope automation

Table 7. Formulation parameters/data

Parameter	Type	Explanation	Units
$Acquire_i$	Data	Cost to acquire Subject i based on their $Ra_{i,v}$ values.	[$/$Subject_i$]
$Ra_{i,v}$	Data	The measured available resources for Subject i on each BPR v.	[BPR_v unit]
$RDF_v^z()$	This non-linear function calls R_D data	The result of this function call is the R_D, or BPR v's value, at performance score $HLTp_i$. In other words, it is the BPR v demanded from Subject i using configuration z based on the argument $HLTp_i$ (performance). This is obtained from a call to a (stepwise-nonlinear) function that relates the y-axis to the argument $HLTp_i$ (the x-axis) for each BPR and HFE configuration.	[BPR_v unit]
$Training\_cost_v$	Data	Training cost to increase the BPR v score by one unit.	[$/$BPR_v$ unit]
HFE_cost_z	Data	Cost to integrate configuration z into the system	[$]

Table 8. User-defined data/constraints

Parameter	Type	Explanation	Units
$HLTp_{max}$	User defined Data	Maximum HLTp value possible. Obtained from the MBHSI experimental results. This is the maximum HLTp score that any of the 64 subjects achieved.	[HLTp units]
$HLTp_{min}$	User defined Data	Minimum HLTp value required by the decision makers. Obtained from User input.	[HLTp units]
$HLTp_{avg}$	User defined Data	Average HLTp value required by the decision makers. Obtained from User input.	[HLTp units]
n	User defined Data	Number of subjects to be selected. Can range from 1 to i-1. Obtained from User input.	none

Table 9. Decision variables

Decision Variable	Type	Explanation	Units
$HLTp_i$	Continuous	Defines how well Subject i must perform.	[HLTp units]
x_i	Binary $\in \{0,1\}$	These are the subjects selected to optimize the formulation.	none

Table 10. MINLP formulation

$Min\ Cost \longrightarrow$ "Select the most affordable subjects (x_i) who have the $Ra_{i,v}$ and can attain the required HLTp while minimizing the costs incurred between the training, personnel, and HFE domains."				
[The columns to the right describe the element of the objective function directly below them]	Training Costs Training cost per unit BPR * the amount of training needed (i.e., how far below the RDF curve the $Ra_{i,v}$ is for a given $HLTp_i$)	Personnel Costs Cost to acquire Subject i, only if the subject is selected (x_i = {0,1})	HFE Configuration Costs Cost of the current HFE configuration	Solve the formulation for each HFE configuration

$$Min \sum_i \sum_v \{ [Training\_cost_v * (RDF_v^z(HLTp_i) - Ra_{i,v})^+] + [Acquire_i * x_i] + [HFE\_cost_z] \} \quad \forall z = 1, 2, \ldots, c$$

s.t.

$HLTp_i$	$\geq$	x_i * $HLTp_{min}$	minimum HLTp
$HLTp_i$	$\leq$	x_i * $HLTp_{max}$	maximum HLTp
$\frac{[\sum_{i=1}^{n} HLTp_i]}{n}$	$\geq$	$HLTp_{avg}$	average HLTp
$\sum_{i=1}^{64} x_i$	$=$	n	number of subjects to select
$HLTp_i$	$\geq$	0	non-negativity constraint
x_i	$\in$	{0,1}	subjects are selected (1) or not (0)

= Decision Variables
= Nonlinear function that calls for the RDF threshold curves

B. MODEL CODE CREATION AND FUNCTIONAL ASSESSMENT

We programmed the formulation in the Julia programming language using the JuMP package. The RDFs were coded as piecewise, nonlinear segments with the segment parameters provided by Taranto's novel R code and experimental data (2020). To solve the full MINLP formulation, we utilized the "SCIP" solver. Upon obtaining a solution, we solved a subsequent model of reduced size that was informed by precisely which participants were selected. In this new model, with the binary selection decisions already set from the original model (i.e., the x_i values are fixed), we arrived at a convex nonlinear program that allowed multipliers for a sensitivity analysis. The "Ipopt" solver was used for the second model and thus the sensitivity analysis.

We wrote the code in an iterative manner using Taranto's (2020) data set and RDFs, and tested it with a simplified data set composed of five subjects and four BPRs. This simplified data set utilized RDFs that were straight lines. Code results were confirmed with results from an Excel spreadsheet. The incorporation of stepwise-nonlinear RDFs increased the complexity of the code significantly. Results were validated via inspection of data sets and intermediate variable values.

C. MODEL PARAMETERS

1. Scenario Selection

The optimization formulation in Table 10 allowed for flexibility in setting up widely varying scenarios that were solved to minimize cost and maximize performance. The general construction of this MP theoretically demonstrated a system-agnostic and DAS life cycle-phase-agnostic approach to HSI optimization. Thus, any parameter could be changed to accommodate the system, phase, or subjects being explored. The common requirement in any particular scenario, however, was performance. Thus, the scenarios explored varied with regard to the minimum and average HLTp, while fixing other parameters.

2. Parameter Selection

Table 11 illustrates the values assigned to the MP variables. Taranto's (2020) experimental data were used to calculate the RDFs. Specifically, his 64 subjects' 17 R_A (BPR scores) and single HLTp were used to determine the stepwise nonlinear RDF curves. For this work, the same 64 subjects' R_A were used in the MINLP. We did this because the R_A scores represented actual human subject scores on the 17 BPRs, and to obviate the need to create subjects with notional PCEs. Those notional subjects might vary from the experimental cohort, and thus bring into question the use of the experimentally determined RDF curves for the notional cohort.

14 of the RDFs for these configurations ($z = 2$ and 3 in our MINLP) were decreased by 25% and 75%, respectively (Table 11), to account for the significant increase in HLTp with HFE in Taranto's C.1 and C.2 configurations (Table 4). These values were likely conservative and were simplifications (i.e., the true value was likely a larger decrease and not a simple factor reduction). This conjecture was based on calculating RDFs from Taranto's data, but was limited given that both configurations C.1 and C.2 had only 7 subjects in each group. BPR 13's RDF was kept unchanged with Configurations 2 and 3, and the RDFs of BPR 1 and 6 were increased 15% for Configuration 2 and 25% for Configuration 3. These adjustments were intended to address the possibility that new HFE configurations would obviate or decrease some BPRs, not affect others, and require an increase in yet others. In the R_D profiles from Taranto (Figure 22), BPR 13 was roughly in the middle third for all HLTp values. The RDFs for BPRs 1 and 6 were selected to increase with the HFE configurations, and both BPRs varied between the middle and top third across the different HLTp values (Figure 22).

Table 11. Formulation variable assignments

<table>
<tr><th>Model Element</th><th>Variables</th><th>Scenario 1 Lowest Performance</th><th>Scenario 2 Low Performance</th><th>Scenario 3 Medium Performance</th><th>Scenario 4 High Performance</th><th>Scenario 5 Highest Performance</th></tr>
<tr><td rowspan="2">HLTp Constraints</td><td>HLTp min</td><td>150</td><td>282</td><td>1500</td><td>5000</td><td>10,000</td></tr>
<tr><td>HLTp avg (= HLTp min*110%)</td><td>165</td><td>310</td><td>1650</td><td>5500</td><td>11,000</td></tr>
<tr><td colspan="7"></td></tr>
<tr><td>GSPT model data</td><td>Baseline RDF curves (Config 1)</td><td colspan="5">Based on Taranto’s experimental cohort</td></tr>
<tr><td rowspan="6">RDF_v^z changes</td><td>HFE 2 25% RDF decrease</td><td colspan="5">BPR 2, 3, 5, 7–12, 14–17</td></tr>
<tr><td>HFE 2 constant RDF</td><td colspan="5">BPR 13</td></tr>
<tr><td>HFE 2 15% RDF increase</td><td colspan="5">BPR 1, 6</td></tr>
<tr><td>HFE 3 75% RDF decrease</td><td colspan="5">BPR 2, 3, 5, 7–12, 14–17</td></tr>
<tr><td>HFE 3 constant RDF</td><td colspan="5">BPR 13</td></tr>
<tr><td>HFE 3 25% RDF increase</td><td colspan="5">BPR 1, 6</td></tr>
<tr><td># Selectees</td><td>n</td><td colspan="5">10</td></tr>
<tr><td rowspan="2">Subject info</td><td># Subjects</td><td colspan="5">64</td></tr>
<tr><td>Subject PCEs</td><td colspan="5">Based on Taranto’s experimental cohort</td></tr>
<tr><td rowspan="5">Costs</td><td>Personnel - Acquire_i values

[$/unit BPR]</td><td colspan="5"><table>
<tr><td>BPR</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td></tr>
<tr><td>Cost</td><td>$55</td><td>$25</td><td>$65</td><td>$0.01</td><td>$60</td><td>$60</td><td>$47</td><td>$30</td></tr>
</table>
<table>
<tr><td>9</td><td>10</td><td>11</td><td>12</td><td>13</td><td>14</td><td>15</td><td>16</td><td>17</td></tr>
<tr><td>$33</td><td>$70</td><td>$55</td><td>$63</td><td>$50</td><td>$47</td><td>$58</td><td>$45</td><td>$100</td></tr>
</table></td></tr>
<tr><td>Training - Training_cost_v values

[$/unit BPR]</td><td colspan="5"><table>
<tr><td>BPR</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td></tr>
<tr><td>Cost</td><td>$48</td><td>$48</td><td>$48</td><td>$0.01</td><td>$62</td><td>$76</td><td>$24</td><td>$57</td></tr>
</table>
<table>
<tr><td>9</td><td>10</td><td>11</td><td>12</td><td>13</td><td>14</td><td>15</td><td>16</td><td>17</td></tr>
<tr><td>$33</td><td>$43</td><td>$52</td><td>$52</td><td>$43</td><td>$90</td><td>$38</td><td>$28</td><td>$100</td></tr>
</table></td></tr>
<tr><td>HFE 1 - HFE_cost₁</td><td colspan="5">$0</td></tr>
<tr><td>HFE 2 - HFE_cost₂</td><td colspan="5">$20,000</td></tr>
<tr><td>HFE 3 - HFE_cost₃</td><td colspan="5">$30,000</td></tr>
</table>

D. SUMMARY

The MP formulated in this section utilizes MBHSI output along with cost data to define the tradespace between the HSI domains of personnel, training, and HFE. The MINLP is versatile and applicable to any system's HLT at any phase in the DAS life cycle. Test scenarios were constructed based on desired HLTp values while the various parameters were chosen based on Taranto's data and augmented with notional data. The final product was an MINLP that modeled the three HSI domains, allowed for quantitative domain trades, and accounted for variable costs, HFE configurations, RDFs, subject data, and HLTp. The next chapter solves the formulation for the five scenarios and interprets the results.

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V. RESULTS AND FINDINGS

The optimization formulation presented in Table 10 allows for tradespace analysis while varying dozens of parameters and constraints over thousands of permutations. For the purposes of this MP, the empirically obtained RDF curves are the only values that are truly fixed. All other parameters can be varied to explore the HSI tradespace. The scenarios chosen for exploration in this chapter fix all parameters except the $HLTp_{min}$ and $HLTp_{avg}$ values. These parameters were chosen because the common requirement in any particular task is the performance required. As the HLTp values increase, the optimization results vary as described below.

A. ANALYSIS

1. Scenario Results

Tables 12 and 13 list the results from running each scenario once for each of the three HFE configurations (described in Tables 5 and 6). Yellow highlights the optimal cost for each scenario. This optimal cost is the solution to the objective function (Table 10), and is a reflection of the optimal selectee sum total costs in each HSI domain.

All scenarios took less than 800 seconds to compute running Julia Version 1.6.1 on a MacBook Pro (2020) with a 2GHz Quad-Core Intel i5. Scenarios 1 and 2 tended to take roughly 30–75% longer than the other scenarios.

Table 12. Scenario 1–3 results

Scenario 1: Minimum HLTp = 150, Average HLTp = 165

HFE Configuration 1

	HLTp	Selectee	Domain Costs		
Selectee Indices	solution	Cost	Trng	Pers	HFE
7	150	$46,341	3%	97%	0%
16	150	$49,042	1%	99%	0%
20	150	$48,066	7%	93%	0%
26	150	$48,511	1%	99%	0%
29	536	$48,567	1%	99%	0%
37	150	$44,895	2%	98%	0%
42	150	$46,994	26%	74%	0%
51	150	$48,183	2%	98%	0%
55	150	$48,110	3%	97%	0%
60	150	$46,098	3%	97%	0%
Composite values	Average HLTp	Total Cost	Scenario Domain Costs		
	189	$474,809	5%	95%	0%

Sensitivity Analysis	
Min HLTp Shadow Cost =	-$33,554
Avg HLTp Shadow Cost =	$0.00

HFE Configuration 2

	HLTp	Selectee	Domain Costs		
Selectee Indices	solution	Cost	Trng	Pers	HFE
7	150	$47,582	2%	94%	4%
16	536	$50,785	0%	96%	4%
20	150	$47,987	2%	93%	4%
26	150	$50,623	1%	95%	4%
29	150	$50,133	0%	96%	4%
37	150	$46,768	2%	94%	4%
42	150	$44,018	16%	79%	5%
51	150	$50,652	3%	93%	4%
55	150	$49,973	3%	93%	4%
60	150	$48,127	3%	92%	4%
Composite values	Average HLTp	Total Cost	Scenario Domain Costs		
	189	$486,648	3%	93%	4%

Sensitivity Analysis	
Min HLTp Shadow Cost =	-$18,358
Avg HLTp Shadow Cost =	$0.00

HFE Configuration 3

	HLTp	Selectee	Domain Costs		
Selectee Indices	solution	Cost	Trng	Pers	HFE
7	150	$48,507	1%	92%	6%
16	536	$51,785	0%	94%	6%
20	186	$48,738	2%	92%	6%
26	150	$52,063	2%	92%	6%
29	150	$51,526	1%	93%	6%
37	150	$47,876	2%	92%	6%
42	150	$40,502	6%	86%	7%
51	150	$52,187	4%	91%	6%
55	150	$51,431	3%	91%	6%
60	150	$49,072	3%	91%	6%
Composite values	Average HLTp	Total Cost	Scenario Domain Costs		
	192	$493,687	2%	92%	6%

Sensitivity Analysis	
Min HLTp Shadow Cost =	-$8,369
Avg HLTp Shadow Cost =	$0.00

Scenario 2: Minimum HLTp = 282, Average HLTp = 310

HFE Configuration 1

	HLTp	Selectee	Domain Costs		
Selectee Indices	solution	Cost	Trng	Pers	HFE
7	282	$47,248	5%	95%	0%
16	536	$49,418	1%	99%	0%
20	282	$49,335	9%	91%	0%
26	282	$49,167	2%	98%	0%
29	536	$48,567	1%	99%	0%
37	282	$46,280	5%	95%	0%
42	282	$49,076	29%	71%	0%
51	282	$48,999	3%	97%	0%
55	282	$48,911	5%	95%	0%
60	282	$46,722	5%	95%	0%
Composite values	Average HLTp	Total Cost	Scenario Domain Costs		
	333	$483,724	7%	93%	0%

Sensitivity Analysis	
Min HLTp Shadow Cost =	-$2,656
Avg HLTp Shadow Cost =	$0.00

HFE Configuration 2

	HLTp	Selectee	Domain Costs		
Selectee Indices	solution	Cost	Trng	Pers	HFE
7	282	$48,418	3%	93%	4%
16	793	$50,785	0%	96%	4%
20	282	$48,739	4%	92%	4%
26	282	$50,910	2%	94%	4%
29	282	$50,472	1%	95%	4%
37	282	$47,131	3%	93%	4%
42	282	$45,386	19%	77%	4%
51	282	$51,308	4%	92%	4%
55	282	$50,630	4%	92%	4%
60	282	$48,597	4%	92%	4%
Composite values	Average HLTp	Total Cost	Scenario Domain Costs		
	333	$492,375	4%	92%	4%

Sensitivity Analysis	
Min HLTp Shadow Cost =	-$2,709
Avg HLTp Shadow Cost =	$0.00

HFE Configuration 3

	HLTp	Selectee	Domain Costs		
Selectee Indices	solution	Cost	Trng	Pers	HFE
7	282	$49,072	2%	91%	6%
16	1,031	$51,785	0%	94%	6%
20	282	$48,831	2%	92%	6%
26	282	$52,261	3%	92%	6%
29	282	$52,106	2%	92%	6%
37	282	$48,082	2%	91%	6%
42	282	$40,803	7%	86%	7%
51	282	$52,664	4%	90%	6%
55	282	$51,908	4%	90%	6%
60	282	$49,270	4%	90%	6%
Composite values	Average HLTp	Total Cost	Scenario Domain Costs		
	357	$496,781	3%	91%	6%

Sensitivity Analysis	
Min HLTp Shadow Cost =	-$2,320
Avg HLTp Shadow Cost =	$0.00

Scenario 3: Minimum HLTp = 1500, Average HLTp = 1650

HFE Configuration 1

	HLTp	Selectee	Domain Costs		
Selectee Indices	solution	Cost	Trng	Pers	HFE
7	1,500	$48,938	8%	92%	0%
10	2,224	$53,068	4%	96%	0%
20	1,500	$51,352	13%	87%	0%
25	2,240	$53,643	7%	93%	0%
26	1,500	$51,170	6%	94%	0%
29	1,500	$49,978	4%	96%	0%
37	1,500	$49,154	11%	89%	0%
42	1,500	$51,628	32%	68%	0%
51	1,536	$50,594	7%	93%	0%
60	1,500	$48,899	9%	91%	0%
Composite values	Average HLTp	Total Cost	Scenario Domain Costs		
	1,650	$508,424	10%	90%	0%

Sensitivity Analysis	
Min HLTp Shadow Cost =	-$27,867
Avg HLTp Shadow Cost =	-$10.73

HFE Configuration 2

	HLTp	Selectee	Domain Costs		
Selectee Indices	solution	Cost	Trng	Pers	HFE
7	1,500	$50,065	6%	90%	4%
16	1,762	$51,708	2%	94%	4%
20	1,500	$50,007	6%	90%	4%
25	2,738	$53,257	2%	94%	4%
26	1,500	$52,021	4%	92%	4%
29	1,500	$51,675	3%	93%	4%
37	1,500	$48,481	5%	91%	4%
42	1,500	$47,229	22%	74%	4%
51	1,500	$52,445	6%	90%	4%
60	1,500	$49,703	6%	90%	4%
Composite values	Average HLTp	Total Cost	Scenario Domain Costs		
	1,650	$506,592	6%	90%	4%

Sensitivity Analysis	
Min HLTp Shadow Cost =	-$20,823
Avg HLTp Shadow Cost =	-$0.87

HFE Configuration 3

	HLTp	Selectee	Domain Costs		
Selectee Indices	solution	Cost	Trng	Pers	HFE
7	1,500	$50,307	5%	89%	6%
16	1,500	$52,108	1%	94%	6%
20	1,752	$49,616	4%	90%	6%
25	1,815	$53,505	1%	93%	6%
26	1,500	$53,094	4%	90%	6%
29	1,500	$53,341	4%	90%	6%
37	2,434	$49,816	6%	88%	6%
42	1,500	$41,775	9%	84%	7%
55	1,500	$52,907	6%	88%	6%
60	1,500	$50,234	5%	89%	6%
Composite values	Average HLTp	Total Cost	Scenario Domain Costs		
	1,650	$506,704	4%	90%	6%

Sensitivity Analysis	
Min HLTp Shadow Cost =	-$5,703
Avg HLTp Shadow Cost =	-$9.43

Table 13. Scenario 4–5 results

Scenario 4: Minimum HLTp = 5000, Average HLTp = 5500

HFE Configuration 1

Selectee Indices	HLTp solution	Selectee Cost	Domain Costs		
			Trng	Pers	HFE
7	5,000	$53,852	17%	83%	0%
10	5,000	$55,769	8%	92%	0%
13	5,000	$60,212	7%	93%	0%
22	5,000	$56,953	3%	97%	0%
26	5,000	$55,867	14%	86%	0%
29	5,000	$54,598	12%	88%	0%
31	10,000	$58,964	9%	91%	0%
49	5,000	$58,022	5%	95%	0%
51	5,000	$54,938	14%	86%	0%
60	5,000	$54,964	19%	81%	0%
Composite values	Average HLTp	Total Cost	Scenario Domain Costs		
	5,500	$564,139	11%	89%	0%

Sensitivity Analysis	
Min HLTp Shadow Cost =	-$14,195
Avg HLTp Shadow Cost =	-$3.51

HFE Configuration 2

Selectee Indices	HLTp solution	Selectee Cost	Domain Costs		
			Trng	Pers	HFE
7	5,000	$53,250	12%	84%	4%
16	5,000	$53,789	6%	91%	4%
20	5,000	$52,502	11%	85%	4%
25	5,000	$54,287	4%	92%	4%
26	5,000	$54,296	8%	88%	4%
29	10,000	$55,278	9%	87%	4%
37	5,000	$51,825	11%	85%	4%
42	5,000	$51,055	28%	68%	4%
51	5,000	$54,637	10%	87%	4%
60	5,000	$52,756	12%	84%	4%
Composite values	Average HLTp	Total Cost	Scenario Domain Costs		
	5,500	$533,675	11%	85%	4%

Sensitivity Analysis	
Min HLTp Shadow Cost =	-$7,035
Avg HLTp Shadow Cost =	-$1.80

HFE Configuration 3

Selectee Indices	HLTp solution	Selectee Cost	Domain Costs		
			Trng	Pers	HFE
7	5,000	$52,164	8%	86%	6%
16	5,000	$53,591	3%	91%	6%
20	5,000	$50,729	6%	88%	6%
24	5,000	$55,740	2%	93%	5%
25	10,000	$54,758	3%	91%	5%
26	5,000	$54,509	7%	88%	6%
37	5,000	$50,076	6%	88%	6%
42	5,000	$43,689	13%	80%	7%
55	5,000	$54,160	8%	86%	6%
60	5,000	$51,950	9%	86%	6%
Composite values	Average HLTp	Total Cost	Scenario Domain Costs		
	5,500	$521,366	6%	88%	6%

Sensitivity Analysis	
Min HLTp Shadow Cost =	-$2,868
Avg HLTp Shadow Cost =	-$0.60

Scenario 5: Minimum HLTp = 10,000, Average HLTp = 11,000

HFE Configuration 1

Selectee Indices	HLTp solution	Selectee Cost	Domain Costs		
			Trng	Pers	HFE
4	10,000	$60,605	11%	89%	0%
7	10,000	$56,735	21%	79%	0%
8	14,015	$63,269	13%	87%	0%
26	14,015	$59,585	20%	80%	0%
29	10,000	$57,171	16%	84%	0%
37	10,000	$57,909	24%	76%	0%
42	10,000	$60,897	43%	57%	0%
51	10,000	$57,700	18%	82%	0%
55	11,969	$59,325	21%	79%	0%
60	10,000	$58,078	23%	77%	0%
Composite values	Average HLTp	Total Cost	Scenario Domain Costs		
	11,000	$591,275	21%	79%	0%

Sensitivity Analysis	
Min HLTp Shadow Cost =	-$3,441
Avg HLTp Shadow Cost =	-$3.86

HFE Configuration 2

Selectee Indices	HLTp solution	Selectee Cost	Domain Costs		
			Trng	Pers	HFE
7	10,000	$54,467	14%	82%	4%
10	14,015	$56,661	6%	90%	4%
16	10,000	$55,115	8%	89%	4%
20	10,000	$53,644	13%	84%	4%
25	10,000	$55,881	7%	90%	4%
29	14,015	$55,841	10%	86%	4%
37	10,000	$53,219	14%	82%	4%
42	10,000	$52,697	30%	66%	4%
51	11,969	$56,076	12%	84%	4%
60	10,000	$54,130	14%	82%	4%
Composite values	Average HLTp	Total Cost	Scenario Domain Costs		
	11,000	$547,733	13%	84%	4%

Sensitivity Analysis	
Min HLTp Shadow Cost =	-$4,873
Avg HLTp Shadow Cost =	-$1.47

HFE Configuration 3

Selectee Indices	HLTp solution	Selectee Cost	Domain Costs		
			Trng	Pers	HFE
7	10,000	$52,639	9%	85%	6%
16	10,656	$54,043	4%	90%	6%
20	10,000	$51,144	6%	88%	6%
25	14,015	$54,960	4%	91%	5%
29	10,656	$55,510	8%	87%	5%
37	10,000	$50,552	7%	87%	6%
42	10,000	$44,251	14%	79%	7%
51	14,015	$55,443	9%	85%	5%
55	10,656	$54,584	9%	86%	5%
60	10,000	$52,364	9%	85%	6%
Composite values	Average HLTp	Total Cost	Scenario Domain Costs		
	11,000	$525,489	8%	86%	6%

Sensitivity Analysis	
Min HLTp Shadow Cost =	-$1,076
Avg HLTp Shadow Cost =	-$0.50

2. Interpretation

The selectees that resulted in the lowest objective function costs were the most efficient (i.e., lowest cost) for the scenarios. Given the parameters for these scenarios, the selectees were primarily those with small PCEs and thus low $Acquire_i$ costs. In fact, the selectees for Scenario 1, HFE Configuration 1 were those with the 10 lowest predicted HLTp scores based on their PCEs. Training to achieve the HLTp is cheap, and only small amounts are required, thus these were the most efficient selectees. Looking at Scenario 4, Configuration 1, however, shows a different cohort of selectees. Many of these still had low PCE values, but Subject 22, for example, had the seventh-highest predicted HLTp based on his/her PCE. It just so happens, that s/he had that combination of R_A's that was relatively cheap to acquire, and it was concomitantly cheap to train her/his limiting BPRs. Interestingly, when $Acquire_i$ costs are scaled down and the $Training\_cost_v$ values are scaled up relative to each other, the new selectees almost uniformly have the highest predicted HLTp scores in the entire cohort, based on their large PCEs. Under those new cost parameters, the selectees with large PCEs are the most efficient to utilize.

Several trends are evident upon inspection of the results in Tables 12 and 13. Given the parameters, as the $HLTp_{min}$ increases, the lowest cost formulation starts at HFE Configuration 1 and tends towards Configuration 3. This trend is due to the increased cost of training being offset by the RDF reductions as a result of the HFE Configurations. This is illustrated by the percentage of training costs for Subject 42 in Scenario 3. His training cost percentage and raw values decreased when Configuration 2 and 3 were calculated. These trends would likely be accentuated if all the BPRs were reduced due to HFE Configurations 2 and 3 and/or if the HFE Configurations had an even larger "flattening" effect on the RDFs (Figure 20).

Other general trends include decreasing shadow cost absolute values for the $HLTp_{min}$ when moving from HFE 1 to HFE 3. Also, most of the selectees were predicted to attain the $HLTp_{min}$ values, with at most three selectees scoring higher in order to enable the cohort to attain the $HLTp_{avg}$ value, as opposed to all the selectees being predicted to attain the $HLTp_{avg}$ value.

3. Sensitivity Analysis

As discussed in Chapter IV, Methods, the sensitivity analysis was limited due to the inherent nature of MINLPs. The sensitivity analysis was conducted on the auxiliary convex program obtained after first solving the MINLP. This convex program admits Lagrange multipliers that provide estimates on the change of total system cost with respect to changes in the $HLTp_{min}$ and $HLTp_{avg}$ constraint values. Tables 12 and 13 list the shadow costs for these $HLTp_{min}$ and $HLTp_{avg}$ constraints. Thus, for Scenario 5, HFE Configuration 1, we see that the objective function decreased at most $3441 for every 1 unit that the $HLTp_{min}$ constraint was decreased. Likewise, the objective function decreased at most $3.86 for every 1 unit that the $HLTp_{avg}$ constraint was decreased. A sensitivity analysis was not possible for the x_i binary variable constraints.

4. Interesting Findings

The MINLP solutions provided a few unexpected results. Scenario 1 and 2's $HLTp_{avg}$ values were greater than the minimum constraint value. We expected these $HLTp_{avg}$ values to be tightly constrained. However, upon inspection of those selectees that forced the $HLTp_{avg}$ to be greater than the constraint value, a trend was noted. Subject 29 in Scenario 1, HFE Configuration 1 illustrates this situation. Subject 29 "should" have had an HLTp value of 300 so that the cohort's $HLTp_{avg}$ value became 165. However, his optimal HLTp value was solved to be 536. Upon inspection, we noted that Subject 29's cost for an HLTp value of 536 or 300 was the same because the RDF curves for the relevant BPRs have a slope of zero between those points. Thus, the solver assigned the value of 536 to Subject 29. We found equivalent situations in all the configurations for Scenarios 1 and 2. These RDF slopes also explain the shadow cost of $0 for the $HLTp_{avg}$ in these scenarios.

Taranto showed that different resources predominated at different levels of performance (2020, p. 166). While varying the parameters of the formulation in practice runs and in the scenarios above, the MINLP solutions demonstrated this same phenomenon by selecting different subjects at different levels of performance. This result could be exaggerated or minimized by varying the parameters of the MINLP.

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VI. DISCUSSION

We demonstrated that it is possible to formulate an MP to efficiently manage training, personnel, and HFE resources based on data and relationships provided by MBHSI and GSPT. The MP (Table 10) and its solutions answered the thesis research questions posed earlier by quantifying the selected HSI tradespace and yielding results which minimized cost for targeted levels of performance for the system described in Taranto's experiment. The MP also lent insight into interesting MBHSI and GSPT phenomena.

A. THE MATHEMATICAL PROGRAM

The empirical relationships defined and obtained from GSPT, MBHSI, and Taranto's MBHSI experiment (Kondraske, 2011; Taranto, 2020) informed our MP formulation. These data and relationships provided the ability to relate HSI domain resources (in the form of human capabilities) with total system performance for a complex task involving multiple underlying BPRs. The MP used in this thesis (Table 10) was just one formulation we considered. We explored several other draft formulations. Variations in the formulations included consideration of other domains, different decision variables, additional indices, etc. The possible resulting formulations were then found to be either overly complicated for this novel work and lacking tractability, or overly simplistic and ultimately representing sorting (vice optimization) problems. Programming began after choosing the formulation with the best balance of tractability and utility.

Programming the formulation in Julia was a non-trivial undertaking. The piecewise-nonlinear nature of the RDF curves posed a particular challenge. These RDFs complicated both the optimization computation and the sensitivity analysis, ultimately requiring a nuanced computational approach. Once we successfully programmed the MINLP in Julia, the choice of solution scenarios presented another challenge.

The solution scenarios in Chapter V, Results, were chosen for three reasons. First, performance is the goal of HSI and DOD systems, thus it follows that performance should be varied across the scenarios to determine the resultant costs and solutions. Second, performance is a decision variable in the formulation and what varied to obtain an optimal solution; thus, enforcing performance constraints allowed precise control over the different scenarios. Finally, defining a problem and determining a desired performance level to solve that problem are critical steps in the SE process. For example, a bridge is built knowing if it is intended for pedestrians, or to support locomotives. Those two bridges require vastly different resources. Likewise, when dealing with the human system, knowing performance requirements is critical.

The final MP is an adaptable optimization model that allows for trades among the training, personnel, and HFE domains using MBHSI and GSPT derived data. The MP is system, task, life cycle, and service agnostic. The formulation can be readily modified and upgraded for different situations by creating new indices and sets, assigning different parameter values as needed, creating new RDFs for populations, BPRs, and tasks of interest, and modifying decision variables and constraints as needed. In other words, it is a versatile model that shows potential to address the complex HSI tradespace. With more research, scaling, and appropriate data, this type of MP may be able to address higher fidelity HSI tradespace challenges.

B. APPLICABILITY AND POTENTIAL

This work utilized the output of MBHSI, especially Functional Requirements 5 and 6 (Figure 10) and completed the "loop" illustrated in Figure 2. According to that image, we create an MP to "improve HSI capacity." If MBHSI was applied at scale and decision makers had similar MPs at their disposal, one could infer the benefits that tools like this provide. For example, assume a program office must ensure that a system performs a given task at a given level for a given maximum cost. If they are able to manipulate HSI resources within the training, personnel and HFE domains, a tool such as this MP could provide insight and prescriptive suggestions to maximize total system performance and minimize cost. This adaptable tool could potentially differentiate the best solutions among the multitude of different possible parameters, configurations, and constraints. Furthermore, these MPs suggest that MBHSI data may be amenable to other tools within the realm of OR.

OR practitioners are specialists in optimization and data analytics. This thesis utilized optimization principles to solve HSI problems using MBHSI data. GSPT data sets currently exist that may be amenable to optimization and other tools from the OR field of study. Both HSI and OR originated to deal with complexity. Using MBHSI and GSPT data, perhaps HSI can utilize OR to solve problems more complicated than the MP presented in this thesis.

C. LIMITATIONS

Table 5 lists the simplifications and assumptions of the model. These simplifications, assumptions, and idealizations strike a balance between model tractability and utility. The following notable items imposed limitations on this MINLP:

- Experimental validity
    - This model was based on a limited data set of 64 individuals with no flying experience accomplishing a very specific flying task.
- Cost parameters
    - All the cost data were notional.
    - Training costs assumed that training on individual BPRs will result in increased HLTp.
    - HFE costs were a single value and were distributed evenly among the selectees.
- Model assumptions and validity
    - HFE changes on the RDFs were deduced based on a small data set (7 subjects).
    - The model is subject to the mathematical limitations on MINLPs, such as limited sensitivity analyses and combinatorial considerations.
- Criteria selection
    - The scenarios, which assigned HLTp value constraints, were chosen without an operational end in mind and only 10 subjects were selected.
    - Subjects were selected solely based on their PCEs.

- The various scenario HLTp values were kept at the low end of the HLTp range, where there were more data, given that the RDF at high values was less accurate.
- HLTp is considered continuous, but in real world situations, this may not be the case.

These simplifications limit generalizability and applicability to the real world. For example, the solutions typically returned 80–90% selectees with the $HLTp_{min}$ value, and 10–20% with higher values in order to satisfy the $HLTp_{avg}$ constraint. Operationally, this may not make sense because one or two very high performers may not have the effect on unit performance that an entire cohort of selectees meeting the average performance would. Thus, decision makers and analysts may need to modify the constraints for operational use. However, note that the formulation essentially becomes a sorting problem if we remove the HLTp average constraint altogether.

Another limitation involved the HLTp range over which the MP will take place. Although this is more of a GSPT limitation, it is plausible that a program manager may want to make tradeoffs calculated for HLTp values that exceed the range of the empirically derived RDFs. This is a problem due to uncertainty in the RDF curve values beyond the empirically derived range of known values.

D. FUTURE WORK

This thesis work represents the first time an MP has been applied to MBHSI, which itself was first published in 2020. Given that both efforts are new and promising, there is ample opportunity for future research work. Examples include the following:

- Rework the formulation to solve for maximum performance subject to budget constraints.
- Add additional HSI domains to the model.
- Add a time component/decision variable to the formulation.
- Increase the fidelity of the cost parameters, to include changes over time and when passing certain BPR values.
- Increase the fidelity of the HFE RDF changes.

- Develop more sophisticated sensitivity analyses.
- Apply MBHSI and the MINLP to a real-world program.
- Research other relevant OR tools that are applicable to the HSI tradespace problem, such as multiobjective functions, minimum cost network flow, efficient frontiers, and goal programming.

E. CONCLUSION

This thesis describes an optimization model that demonstrates the potential to address the tradespace problem between select HSI domains. The model is system, task, and life cycle phase agnostic, and was informed by the data and relationships provided by MBHSI and GSPT. Solving the MINLP using notional parameters and an experimental data set resulted in an actualization of the goal of HSI: minimal cost and optimal performance. Similar MPs may be applicable to real-world HSI tradespace problems after future work and research in this area by systems engineers, HSI practitioners, and OR experts. If these MPs can be scaled and utilized at the program, service, and DOD level, they may be able to help decision makers increase total system performance and decrease costs substantially.

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APPENDIX

Among the numerous formal definitions and explicit objectives of HSI laid out in DOD policy, optimization and trade-off analyses are omnipresent themes. The following are a few select definitions and objectives of HSI from primarily DOD sources. Note that derivatives of the words "optimize" and "minimize" are italicized in this appendix.

The Defense Acquisition System, DODD 5000.01, September 2018

> The goal [of HSI] will be to *optimize* total system performance and total ownership costs, while ensuring that the system is designed, operated, and maintained consistent with mission requirements. (DOD, 2018, p. 8)

Human Systems Integration in Defense Acquisition, DODI 5000.PR (Draft), 2020

The draft version of DODI 5000.PR was written to replace the DODI 5000.02 Enclosure 7 (see below). The 5000.PR defines HSI as providing "a disciplined, unified, and interactive approach to integrate human considerations into system design to *optimize* total system performance and *minimize* life-cycle costs" (DOD, 2020b, p. 3).

Engineering of Defense Systems, DODI 5000.88, November 18, 2020

As an HSI requirement, the lead systems engineer will "use a human-centered design approach for system definition, design, development, test, and evaluation to *optimize* human-system performance" (p. 23).

Operation of the Adaptive Acquisition Framework, DODI 5000.02, Enclosure 7, 2017

This enclosure describes the goal of HSI: "To *optimize* total system performance and total ownership costs, while ensuring that the system is designed, operated, and maintained to effectively provide the user with the ability to complete their mission" (2017b, p. 19).

Defense Acquisition University

The Defense Acquisitions University's (DAU's) definition highlights the domains of HSI, as well as optimization of performance and minimization of cost:

> HSI's objective is to provide equal consideration of the human element along with the hardware and software processes for engineering a system that *optimizes* total system performance and *minimizes* total ownership costs (Defense Acquisition University [DAU], n.d., chapter 5, p. 1).

Naval Postgraduate School

NPS is the DOD's only academic program to offer graduate degrees and certificates in HSI. NPS defines HSI as "an interdisciplinary approach that makes explicit the underlying trade-offs across the HSI domains, thereby facilitating *optimization* of total system performance in both non-materiel and materiel solutions to address the capability needs of organizations" (Tvaryanas & Shattuck, 2010, p. 1). Of note, NPS's HSI program is part of the Operations Research (OR) Department, a discipline that specializes in optimization techniques.

Naval Postgraduate School's HSI Curriculum, July 27, 2021

Trade-offs between HSI domains are a key method for achieving optimization, thus the HSI curriculum at NPS emphasizes the role of optimization and trade-offs:

> Human Systems Integration (HSI) acknowledges that the human is a critical component in any complex system. It is an interdisciplinary approach that makes explicit the underlying tradeoffs across the HSI domains, and other engineering disciplines, logistics, acquisition, and T&E, *optimizing* total system performance while *minimizing* total ownership costs (2021).

The curriculum description goes on to explicitly emphasize the importance of tradeoffs in three of the six HSI core competencies listed: "Analytical Techniques," "Modeling and Simulation," and "Implementing HSI Tradeoffs."

The Author's Definition

In the first formal course of this researcher's HSI education, the first assignment was to define HSI, in accordance with the International Council on Systems Engineering (INCOSE) guiding criteria (Deal, 2007) and based on various background readings. This researcher penned the following:

> HSI is a validated Systems Engineering discipline by which all human considerations are addressed iteratively throughout the life cycle of a system.

- The human considerations arise from those who operate, maintain, and support the system, and by their designed interactions with that system.
- These comprehensive considerations are analyzed via the framework's domains of manpower, personnel, training, human factors engineering, survivability, safety & occupational health, environment, and habitability.
- Decision makers, managers, and engineers utilize this framework to best coalesce the trade-offs required by these domains, in order to *maximize/ optimize* total system performance and affordability.

It is interesting that even after only a few hours of formal instruction, the concepts of trade-offs and the importance of optimization were clear to this novice HSI student.

The services and multiple other organizations the DOD have their own definitions of HSI, each incorporating the themes of tradeoffs and optimization. Furthermore, other U.S. governmental organizations, such as the Department of Homeland Security and National Aeronautics and Space Administration, along with Canadian and British organizations also include the concepts of tradeoffs and optimization in their descriptions of HSI.

International Council on Systems Engineering

INCOSE is a non-DOD, international SE advocacy organization that acknowledges the role and discipline of HSI. Although its view of HSI differs somewhat from that of the DOD, it is instructional to see that INCOSE defines HSI as "interdisciplinary technical and management processes for integrating human considerations within and across all system elements; an essential enabler to systems engineering practice" (INCOSE, 2020). This characterization is congruent with the DOD's definition, which acknowledges SE as the containing system for HSI, whose outputs enable SE.

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